PHD

Designing Emotionally Expressive Behaviour: Intelligibility and Predictability in Human-Robot Interaction

Novikova, Jekaterina

Award date:
2016

Awarding institution:
University of Bath

Designing Emotionally Expressive Behaviour: Intelligibility and Predictability in Human-Robot Interaction

submitted by

Jekaterina Novikova

for the degree of Doctor of Philosophy

of the

University of Bath

Department of Computer Science

February 2016

Signature of Author ....

Jekaterina Novikova

ACKNOWLEDGEMENTS

I would love to express my sincere gratitude to my supervisor Dr. Leon A. Watts, for his extraordinary support throughout the past few years. I would also like to thank my co-supervisor Dr. Joanna Bryson and my internship's supervisor Dr. Tetsunari Inamura, for their support during my PhD. I would like to express my appreciation to the colleagues and friends in the department of Computer Science at the University of Bath, for their support and help both personally and professionally. I would also like to thank the University of Bath. This research would not have been possible without the funding of a Research Studentship, as well as the support of excellent facilities and staff members from the University. Finally, special thanks go to my family and parents for their love and support. It is a long journey to complete this PhD and my family have kept me encouraged throughout.

ABSTRACT

In the emerging world of human-robot interaction, social robotics has become ever more important. Social robotics is a fundamental area in such domains as healthcare and medical robotics, consumer robotics or service robotics. Social robots working among humans should be able to communicate naturally with people using not only verbal but also non-verbal signals. Some cues of non-verbal body language, associated with affect and emotions, have an evolutionary root in humans that allows them to signal their unobservable internal state and intentions to others around them. An ability to interpret an internal state and intentions of team-members or counterparts is important not only in human-human but also in human-robot teams. One possible way to contribute to understandability is for robots to make their otherwise unobservable internal state interpretable to people through the use of emotionally expressive body language. This makes robots more predictable, acceptable and likeable, thus, in the end, having a potential to make them more effective team-players.

This thesis addresses the problem of enabling humans to better understand machines by examining the role of artificial emotions synthesized and expressed by robots in the process of human-robot interaction. In our first study, we probe whether it is possible to signal a wanted emotional meaning through bodily expressions of a non-humanoid robot. The results provide strong support for the potential utility of bodily expressions in robots for communicating emotional meaning to people. A set of design parameters was developed from an analysis of research on non-verbal expression of emotion in the animal world. In the next two studies, we explore how this set of design parameters impacts how people perceive the emotional meaning of a robot expression, and investigate the nature and dynamics of peoples' perception of emotion expressed in a robot through its bodily movements. The results provide the basis for a mapping between the different design parameters of a robot's bodily expression and emotional interpretations. In addition, the results of the study show that people perceive emotionally expressive robots as more anthropomorphic, more animate, more likeable, more responsible and even more intelligent. In two next studies we investigate two major factors that may have influence on the perception of robot emotions. In one study, we investigate how the particular situational context in which expressions are used by the

robot influences how they are perceived and interpreted by people. Another major factor to investigate is how the morphology of a robot performing emotional expressions influences how these expressions are interpreted and whether people are consistent in the emotional meaning they perceive. Finally, having a coherent design scheme to produce meaningful emotional expressions through robot body movements, we investigate in our last study the impact of such expressions on people's attitudes towards a robot. The results of the work provide evidence of the impact of the robot's emotional expressiveness on the perception of their anthropomorphism, animacy, likeability and intelligence.

Results of our work are discussed in terms of the utility of expressive behaviour for facilitating human understanding of robot intentions and the directions for the future development in the design of cues for emotionally expressive robot behaviour.

PUBLICATIONS

The contribution of the work presented in this thesis has been recognised through peer-reviewed publications in the following scholarly outlets:

- **J. Novikova**, G. Ren, L. Watts (2015): It's Not the Way You Look, It's How You Move: Validating a General Scheme for Robot Affective Behaviour, in *Proceedings of Human-Computer Interaction - INTERACT 2015*, pp. 239-258. Bamberg, Germany

- **J. Novikova**, L. Watts, T. Inamura (2015). Emotionally Expressive Robot Behavior Improves Human-Robot Collaboration. In *Proceedings of the 24th IEEE International Symposium on Robot and Human Interactive Communication RO-MAN'15*, pp.7-12. Kobe, Japan

- **J. Novikova**, L. Watts, T. Inamura (2015). Modeling Human-Robot Collaboration in a Simulated Environment. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction HRI'15*, pp. 181-182. Portland, USA

- **J. Novikova**, L.Watts, J.Bryson (2014). The Role of Emotions in Inter-Action Selection, In *Interaction Studies*, 15:2, pp. 216–223.

- **J.Novikova**, L.Watts (2014). Towards Artificial Emotions to Assist Social Coordination in HRI, In *International Journal of Social Robotics*, Vol. 7:1, pp. 77-88

- **J.Novikova**, L.Watts (2014). A Design Model of Emotional Body Expressions in Non-humanoid Robots, in *Proceedings of Human-Agent Interaction HAI 2014*, pp. 353-360. Tsukuba, Japan.

- Koutsombogera, M., Al Moubayed, S., Beskow, J., Bollepalli, B., Gustafson, J., Hussen-Abdelaziz, A., Johansson, M., Lopes, **J., Novikova**, J., Oertel, C., Skantze, G., Stefanov, K., Varol, G. (2014) The Tutorbot Corpus – A Corpus for Studying Tutoring Behaviour in Multiparty Face-to-Face Spoken Dialogue.

In *Proceedings of the Language Resources and Evaluation Conference LREC'14*. 2014, Reykjavik, Iceland

- Al Moubayed, S., Beskow, J., Bollepalli, B., Gustafson, J., Hussen-Abdelaziz, A., Johansson, M., Koutsombogera, M., Lopes, J., **Novikova, J.**, Oertel, C., Skantze, G., Stefanov, K., Varol, G. (2014) Human-robot collaborative tutoring using multiparty multimodal spoken dialogue. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction HRI'14*, pp. 112-113. Bielefeld, Germany

- Al Moubayed, S., Beskow, J., Bollepalli, B., Hussen-Abdelaziz, A., Johansson, M., Koutsombogera, M., Lopes, J., **Novikova, J.**, Oertel, C., Skantze, G., Stefanov, K., Varol, G. (2014) Tutoring Robots: Multiparty multimodal social dialogue with an embodied tutor. *Innovative and Creative Developments in Multimodal Interaction Systems*, pp. 80-113

- **J.Novikova**, L.Watts (2013): Artificial Emotions to Assist Social Coordination in HRI, in *Workshop on Embodied Communication of Goals and Intentions at the International Conference on Social Robotics (ICSR) 2013.* Bristol, UK

- **J.Novikova**, S.Gaudl, and J.Bryson (2013) Emotionally Driven Robot Control Architecture for Human-Robot Interaction, In *Proceedings of the 14th Conference on Advances in Autonomous Robotics, TAROS'13*, pp.261-263, Oxford, UK

CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Motivation

In the last several decades between 1990s and 2015 most of the robotics research and development has been conducted with industrial robots having a purpose to automate manufacturing. However, robots started to appear in the early 2000s with design intended for use in everyday life in the roles of vacuum cleaners, museum guides or artificial pets. It is most likely that in the future more robots will be introduced to work in our houses and offices rather than as industrial robots working in factories [162]. Many authors have discussed both technical and non-technical challenges and gaps considering potential advancements in the field of robotics. The U.S. robotics roadmap [149], for example, considers progress in the field of robotics in several specific technology areas that depend upon advances in human-robot interaction (HRI). The roadmap includes description of robotics challenges and gaps, and five, ten, and fifteen year goals for advancement possible with research and development. The Strategic Research Agenda (SRA) for robotics in Europe [170] additionally includes an overview of the robotics market in Europe and discussion of underlying technologies used in robotics, with description of the state of the art and 2020 target. Both these organizations emphasize the importance of social robotics and human-robot interaction in daily life, considering such domains as healthcare and medical robotics, consumer robotics or service robotics.

The environment in which an industrial robot is working completely differs from the type of environment in which humans are working and interacting in the daily life. As a result, robots working among humans should also differ from the industrial ones. A factory is an organized environment with predefined tasks and the industrial robots working there are usually physically separated from humans for the purpose of human safety. Working in close collaboration with humans, on another hand, requires more advanced skills from robots. Collaboration involves the coordination of effort between all the agents which are engaged in a joint activity. In addition to the necessary functions of sensing, orienting in the environment and moving, the robot may benefit from exhibiting a social behaviour and being able to communicate with humans at the appropriate level of abstraction according to situational context. For the purposes of this thesis social behaviours will be treated as any aspect of an agent's behaviour from which an observer might draw inferences about their internal state with respect to the progress of their joint activity. Social robots will need to be able to communicate naturally with people using not only verbal but also non-verbal signals. They will need to engage us not only on the cognitive level, but on an emotional level as well [163].

The social communication, however, is not only important for the purpose of engaging humans into interaction with a robot. Most social interactions depend on one participant's perceptions of specific social dimensions of the other participant. For example, a museum visitor must trust the museum's guides before he will follow their suggestions. An astronaut cannot effectively contribute to a team unless her team–mates both respect her competency and trust that her intentions align with the team's. Ten challenges were proposed by [89] for making automation a "team player" in joint human–agent activity. The one which is addressed throughout this thesis is stated as: *To be an effective team player, intelligent "agents must be able to make pertinent aspects of their status and intentions obvious to their teammates".* [89, p. 93]

Status here is understood as an internal state of an agent, which is normally hidden from the observer, the same as intentions. To make their actions sufficiently predictable, agents must make aspects of their own targets, states, capacities, intentions, changes, and upcoming actions obvious to the people and other agents that supervise and coordinate with them. This means signalling relevant aspects of their internal state to a collaborator.

Humans and animals have evolutionarily developed tools and methods that make their otherwise unobservable internal state and intention interpretable to others around them. Many of these tools are related to non-verbal bodily communication as explained by [3], e.g. when an animal intends to submit to another it may make appeasement signals by cowering, curling up, holding out a hand, facing away or lowering the eyes. Posture is a good example of signalling an internal state: the way an animal sits, stands, or walks reflects and communicates its emotional state and its attitude to the others present. Moreover, changes in bodily appearance usually signal information about an animal's internal state. For instance, some fish and birds can change their colour and size under the influence of temporary emotional states. Human psychology research also clearly indicates that much information about a person's affective states, status and attitude, cooperative and competitive nature of social interaction, and interpersonal intimacy is expressed and accurately communicated to others in non-verbal expressive behaviour [168].

An internal state in humans and animals is inseparable from affect or emotions [25, 115], that are also often expressed using non-verbal behaviour. Numerous demonstrations have shown that people can voluntarily express various emotions with their vocal and/or facial expressive behaviour in such a way that their expressive behaviour can be accurately interpreted by observers [168, 48]. Some social observers [66] have proposed that the ability to manage expressive presentation is a prerequisite to effective social and interpersonal functioning. Amongst the range of expressive behaviours, body language is the focus of this thesis.

An ability to interpret the internal state and intentions of team-members or counterparts is important not only in human-human but also in human-robot teams. On the one hand, some recent experiments in HRI show that people feel more anxiety toward a robot if the robot does not make itself transparent in terms of explaining its state [117]. On another hand, robots that are able to express their status and intentions often positively influence humans attitude towards them [116], [117].

Furthermore, given the prominent tendency for humans to treat machines as social agents and apply human-social models to these in order to understand their behaviour, and the important role that emotions play in living creatures, the modelling of emotion at both a computational/cognitive levels, as well as at a behavioural level has been deemed to be vital for establishing effective and engaging human-computer interaction (HCI) and HRI [135, 24]. The work in this thesis is concerned with this issue as well as with the [89] "team player" challenge stated previously. We address the challenge primarily in terms of a scheme for a robot's control system to maintain a model of its own goal-related internal state. Thus, this thesis is formulated as follows:

> *In order to be understandable, robots must be able to make their otherwise unobservable internal state interpretable to people through the use of emotionally expressive body language. This could make robots more predictable, acceptable and likeable, thus, in the end, making them more effective team-players.*

1.2 Objectives and Research Questions

The main objective of this work is to address the problem of enabling humans to better understand machines by examining the role of artificial emotions synthesized and expressed by robots in the process of human-robot interaction.

The following general questions are formulated and addressed in this thesis:

RQ1: Do people perceive robotic bodily expressions as having different emotional meanings, and if so, are people consistent in the meaning they perceive?

RQ2: Can emotionally-charged robotic bodily expressions be designed and generated in a systematic pre-structured manner to evoke a desired emotional interpretation?

RQ3: What factors impact how people interpret the emotionally-charged bodily expressions of a robot?

RQ4: What are the effects of robotic emotional bodily expressions on people's attitude towards a robot?

These questions are addressed as follows through the thesis. Firstly, the concept of emotion is discussed in the literature review in Chapter 2 and the formal definition of the term is given, together with a brief review of the existing psychological theories of emotion and their role in nature. The purpose of such a review is to distinguish emotions from other affective terms often used in psychology research and to prepare a background for linking natural emotions to artificially synthesized ones. The previous work on emotions and emotional expressions in robots is then presented, emphasizing the lack of research investigating the link between robot body movements and emotional meaning people perceive in such robots, especially in non-humanoid ones. Also, related work regarding people's attitude towards and behaviour with emotionally expressive robots is reviewed as this likely has some useful insights regarding how different bodily expressions of robots can make them more effective in interacting with humans.

Next, a review of the experimental tools that have been used in this research are presented and detailed in Chapter 3. Firstly, we give the review of three approaches to present emotional expressions of robotic agents: interaction with a physical robot, video recordings of a robot, and a simulated computer-based robotic agent. The issues surrounding these approaches are discussed in order to highlight the limitations and benefits of each of them. This is followed by a description of two non-humanoid robots and one humanoid simulated robotic agent used as the platform for the experimental studies. Finally, we review the two main approaches to representing and recognizing emotion, discrete categories and emotional dimensions, and explain why both of these were drawn upon to inform the data collection activities in the following experimental studies. All these issues hold great relevance when it comes to the study of emotion in general, and specifically here, through robot bodily expressions.

Having non-humanoid robotic platforms to use in this research, first it is important to probe whether it is possible to signal the wanted emotional meaning through bodily expressions. This is the focus of two studies presented in Chapter 4. The results provide strong support for the potential utility of bodily expressions in robots for communicating emotional meaning to people.

Having developed a means to create and manipulate the various features of bodily expressions, it is important to provide a systematic approach to developing emotions in robots in terms of a computational model of emotion that links robot actions to emotional expressions. It is also important to develop a more general design scheme that is capable of mapping different features of bodily expressions to a desired emotional interpretation. Having developed such a scheme, it is necessary to perform an exploration into how the different design parameters impact how people perceive the emotional meaning of a robot expression, and into understanding the nature and dynamics of peoples' perception of emotion expressed in a robot through its bodily movements. This work is presented in chapters 5 and 6. These explorations provide data that reveals the underlying relationships between the different design parameters of a robot bodily expression and how these relate to different emotional interpretations and provide the basis for a mapping between them.

Having established the impact that a robot's bodily movements have upon how people perceive robot emotions, and how the different design parameters of an expression influence the emotional meaning that is conveyed, the next major factor to investigate is how the particular situational context in which expressions are used by the robot influences how they are perceived and interpreted by people. Another major factor to investigate is how the morphology of a robot performing emotional expressions influences how these expressions are interpreted and whether people are consistent in the emotional meaning they perceive. This is reported in chapters 7 and 8.

Finally, having a coherent design scheme to produce meaningful emotional expressions through robot body movements, it is important to investigate the impact of such expressions on people's attitudes towards a robot. People's attitudes towards an emotionally expressive robot are explored and analysed in Chapter 6 with a non-humanoid robot signalling different emotions to human observers. The findings of this exploration are later validated using a robot of a different morphology expressing the same emotions in Chapter 8.

1.3 Structure of the Thesis and Contributions

The structure of the rest of this thesis is outlined below, giving a brief description of the theme and context for each chapter.

Chapter 2. Emotions in Nature and in Robotics

In Chapter two we present the concept of emotion and provide a formal definition of the term for use in HRI research. We distinguish emotions from such terms as affect, mood or attitude that are sometimes used interchangeably in the human-robot interaction research, to focus on the temporal characteristics of affective response to task-relevant events in joint activity. Next, we review the existing literature on psychological theories of emotion, such as discrete, dimensional and appraisal theories, thus preparing a base for linking natural emotions to artificially synthesized ones. Later in the chapter we provide a deeper and extensive background regarding emotional body language as it appears in animals and humans, introducing the state of the art research on emotionally expressive body movements in humanoid and non-humanoid robots. We highlight some gaps in research investigating the link between robot dynamic body movements and the emotional meaning people perceive in it. There are very few studies on the design of robotic emotions expressed through body language, especially for non-humanoid forms of robots. There is also a gap in the literature between high-level design guidelines for robotic emotional expression using a body language and the implementation of expressive movements into specific robots. Finally, we review prior work on people's attitudes towards social robots as these are likely to play a role in determining the effectiveness of robot bodily expressions in interactions with humans.

Chapter 3. Method

The methods that have been used in this theses are detailed in Chapter three. It begins with an overview of three commonly used approaches to presenting emotional expressions of robots to observers: using physical robots, using video recordings and robotic simulations. The pros and cons of each approach are discussed with respect to the four research questions to be addressed. A description of the three robotic platforms and the manner in which they have been used in this work follows this. Finally a discussion regarding the tools for measuring emotion is presented, and the measuring tool of choice - Self Assessment Manikin - and its use is detailed.

Chapter 4. Towards Emotional Expressivity in Robots: Preliminary Exploratory Studies

Chapter four presents two studies aiming to understand whether a non-humanoid robot can express artificial emotions in a manner that is meaningful to a human observer. The first study is based on judgements of static images and suggests that they can convey emotional meaning of the presented robot's state. However, static images fail to convey this consistently. Consequently, the second study focuses on the dynamic production of embodied robot expressions. Mixed-methods approach to the problem is presented, combining statistical treatment of ratings data and thematic analysis of qualitative data. The findings from these two studies demonstrate that even very simple movements of a non-humanoid robot can convey emotional meaning. In particular, this suggests that when people attribute emotional states to a robot, they typically apply an event-based frame to make sense of the robotic expressions they have seen. Artificial emotions with high arousal level and negative valence are relatively easy for people to recognise compared to expressions with positive valence. In this chapter, the potential for using motion in different parts of a non-humanoid robot body is discussed to support the attribution of emotion in HRI, towards the design of artificial emotions that could contribute to the efficacy of joint human-robot activities.

The explorations and analysis presented in this chapter resulted in the journal publication [121].

Chapter 5. Emotionally Driven Robot Control Architecture for Human-Robot Interaction

The preliminary studies depend on individually crafted expressive behaviours. Chapter five focuses on the value of an underlying model as an artificial analogue of natural emotion to ground the meaning of an expressive behaviour in the live state of an agent. It presents an emotionally-based computational model of action selection to control robot behaviour in human-robot interaction scenarios. We have implemented the described model as a proof of concept. The physical robot with an implemented model has successfully interacted with the environment and was able to express its internal emotional state and to change its behaviour dynamically according to the implemented actions' interruptions scheme. However, the presented model of emotional action selection raises several design-related concerns: 1) it is not clear what should be the relation between the discrete emotional state and the emotional dimensions of valence, arousal and dominance, 2) it still is an open question how to design the emotional expressions in robots that would be understandable by human observers.

The explorations presented in this chapter resulted in the conference publication [118].

Chapter 6. Design Scheme for Modelling Emotionally Expressive Robot Body Movements

Chapter six builds on Chapter five by presenting a design framework for modelling emotionally expressive robotic movements. The framework combines approach-avoidance with Shape and Effort dimensions, derived from Laban [93], and makes use of anatomical body planes that are general to both humanoid and non-humanoid body forms. An experimental study is reported in this chapter with 34 participants rating an implementation of five expressive behaviours on a non-humanoid robotic platform. The results demonstrate that such expressions can encode basic emotional information, in that the set of Design Parameters (DPs) of the proposed design model can convey the meaning of emotional dimensions of valence, arousal and dominance. The framework thus creates a basis for implementing a set of emotional expressions that are appropriately adapted to contexts of human-robot joint activity.

The explorations and analysis presented in this chapter resulted in the conference publication [120].

Chapter 7. Effect of Context on Interpreting Emotional Robot Body Movements

Chapter seven presents a further analysis of the study reported in chapter six and focuses on the interaction between situational context and emotional body language in robots. The effect of such contextual information on interpreting emotional robot body movements is presented in comparison to the effect of the emotional signals. The results of the study partly support the hypothesis that the emotional signal expressed through bodily movements of a robot overrides the one produced by a situational context.

Chapter 8. Validating the Design Scheme on Robots of Different Expressivities

Chapter eight presents and discusses the idea of using a predefined and universally applicable set of capabilities to assess the expressivity of robot designs. Additionally, this idea is extended to characterize new expressions by combining these capabilities on a timeline. An experimental study reported in this chapter aims to validate on robots of different morphologies and different levels of expressivity the general scheme for creating emotionally expressive behaviours, which was earlier presented in chapter six. The results of the validation study show both the similarities and differences in the perception of valence, arousal and dominance after applying the design scheme to non-humanoid robots of different expressivity. The Energy and Approach/Avoidance group of DPs were robust across the two robot forms. However, our data suggest a need for a more considered mechanism for describing combinations of parameters, especially in terms of the frequency and intensity of expressive behaviours.

The explorations and analysis presented in this chapter resulted in the conference publication [1].

Chapter 9. Discussion

Chapter ten discusses the key findings and contributions of this research with regards to the four research questions addressed in this thesis. The primary original contributions of this work are summarised as follows:

- The development of a new scheme for designing emotionally expressive body movements in robots of different body forms.
- Original findings on the insignificant role of the context as a factor that may impact people's interpretations of the emotionally charged bodily expressions of a robot.
- Original findings on the effects robotic emotional bodily expressions have on people's attitudes towards a robot. People's judgements on emotionally expressive robots are significantly higher on the measurements of four key concepts in HRI: robot's anthropomorphism, animacy, likeability and perceived intelligence.

The chapter also reflects upon the aspects that are related to the limitations of the thesis, as well as in the broader sense. Finally, this chapter describes further work that could be undertaken in the future.

CHAPTER 2

EMOTIONS IN NATURE AND IN ROBOTICS

> Everyone knows what an emotion is,
> until asked to give a definition.
> Then, it seems, no one knows.
>
> Fehr and Russell, 1984

2.1 Introduction

This thesis addresses the potential for an artificial embodied system to generate emotionally expressive behaviours, such that they may be understood by a human observer. This chapter serves to sketch a theoretical and practical background of the concept of emotion and how it may be represented through bodily movements. It begins with a brief definition and formalisation of what emotions are and are not, and what distinguishes them from other affective states, particularly with respect to psychological theories of emotion in people and animals. This is followed by a discussion of how emotions are expressed in humans, especially using bodily movements and gestures. The Laban movement analysis system is presented at this point as an illustration of how specific features of bodily movements provide emotionally-rich background to human body language. Although the Laban system was created for dance, it helps provide more tangible and concrete examples of the type of emotional expressions that are the focus of this research. Following this, the general motivations and potential applications of emotions in social agents are then outlined.

A review of research on emotional expression in robots through different modalities is then presented, drawing particular attention to a great variance of robotic forms and expressive abilities. Furthermore, in this review, certain links between methods developed to facilitate the design of emotional expression and the methods used to present a specific emotional state to an observer are highlighted, as some of these have been overlooked in previous works. The role of environmental context, in which the emotional state of a robot is being expressed, is also discussed in this review as a potential constraint on the universal intelligibility of emotionally expressive behaviour.

The review then moves on to consider previous work on the use of emotions in social robots, charting the developments that have already been made. This work is then discussed and important gaps in the research are highlighted, as these have influenced the manner in which the work informing this thesis has been conducted.

Finally, a note on the ethical implications of using artificial emotions in social robots is presented and discussed, as this justifies the use of emotions with respect to this thesis as an attempt to develop more intuitively understandable and more attractive robotic agents.

2.2 Concept of Emotion

This section reviews the main theories of emotion to try to understand which phenomena are covered by the term *emotion* and what the links between emotions and bodily expressions are.

2.2.1 Definition of Emotion: What It Is and What It Is Not

There are many terms in the research literature on affect describing what we generally refer to as *emotions*. Kleinginna [139] considers 92 different definitions given by researchers organized to different categories, ranging from their relation to physiological components or emotional behaviours to definitions based upon motivational and adaptive views. The concept of affect and emotion is so broad that it allows researchers to develop definitions on different levels of abstraction and describe the phenomena through many different perspectives. This is why it is difficult to reach consensus in the characterization of affect in general and emotion in particular [**?**].

Many researchers stress the episodic nature of emotion [52], [61], [155] that last from under a minute to a few minutes. The episodic character of emotion is in contrast to other affective terms like mood or feeling, that have a longer duration and last for hours, days or even longer [122], [167], [53], [175]. However, there exist more differences between emotion and other affective phenomena, such as higher level of intensity, more specified focus on events, higher rapidity of change and stronger behavioural impact [62]. Table 2.1 presents an overview of an up-to-date research that contrasts emotions to other affective states based on a set of these characteristics. As Table 2.1 shows, when comparing emotion with mood, attitude or personality, emotion is the most intense affective state having the shortest duration. At the same time, emotion has the highest focus on a corresponding event, while e.g. attitude and personality are not

Affective State	Intensity	Duration	Event Focus	Rapidity of Change	Behavioural Impact
Emotion	++ → +++	+	+++	+++	+++
Mood	+ → ++	++	+	++	+
Attitude	0 → ++	++ → +++	0	0 → +	+
Personality	0 → +	+++	0	0	+

Table 2.1: *Comparison of emotions and other affective states. Symbols indicate the degree to which the features are present, with 0 indicating the lowest (absence) and +++ indicating the highest. Arrows → indicate hypothetical ranges. Partly adapted from [156].*

event-focused at all. In terms of rapidity of change and behavioural impact, emotion is a leader among other affective states, as it is the most rapidly changing state having the highest impact on the behaviour associated with this emotion. In general, emotion can be defined as a relatively brief episode of responses by many organismic subsystems to the evaluation of external or internal event as being of major significance [156]. That is to say, emotional state is more likely to influence the next action an agent may take than any other affective state. In HRI, then, it may serve as a helpful cue for a person to predict the likely behaviour of a robot with which they are interacting.

2.2.2 Theories of Emotion

Theorists of affect attempt to describe the irreducible elements of emotion. The most important approaches are presented by two schools of thought: those that view the range of emotional phenomena as a set of discrete emotions, and those which take on the perspective that emotions can be further reduced to unique combinations of a small number of orthogonal dimensions [177]. Next, we will discuss each of these schools in more details.

Categorical Theories and Basic Emotions

Some theoreticians with an evolutionary perspective believe that evolution and adaptation have played a central role in shaping the emotions' characteristics and functions. This theoretical approach is based on the key discoveries of Darwin in terms of the facial expression of emotions [45]. In his book, *The Expression of Emotions in Man and Animals*, Darwin describes emotional facial expressions as innate and universal and emphasized not only their communicative function, but also their evolution in relation to the direct environment. The majority of authors who adopt the evolutionary approach consider anger, fear, joy, sadness and disgust to be basic emotions, although this is a contentious subject, in particular with regard to surprise. More complex emotions would therefore originate as a mixture of these basic emotions [126].

There exist many different theories of Basic Emotions. Each of them selects a different set of fundamental emotions and provide a specific reason of why the selected

Reference	Set of Fundamental Emotions	Basis for inclusion
Arnold (1960)	anger, aversion, courage, dejection, desire, despair, fear, hate, hope, love, sadness	Relation to action tendencies
Ekman, Friesen and Ellsworth (1982)	anger, disgust, fear, joy, sadness, surprise	Universal facial expressions
Frijda (1986)	desire, happiness, interest, surprise, wonder, sorrow	Forms of action readiness
Gray (2009)	rage and terror, anxiety, joy	Hard-wired
Izard (1977)	anger, contempt, disgust, distress, fear, guilt, interest, joy, shame, surprise	Hard-wired
James (1884)	fear, grief, love, rage	Bodily involvement
Mowrer (1960)	pain, pleasure	Unlearned emotional states
Oatley and Johnson-Laird (1987)	anger, disgust, anxiety, happiness, sadness	Do not require propositional content
Panksepp (1982)	expectancy, fear, rage, panic	Hard-wired
Plutchik (1994)	acceptance, anger, anticipation, disgust, joy, fear, sadness, surprise	Relation to adaptive biological processes
Tomkins (1984)	anger, interest, contempt, disgust, distress, fear, joy, shame, surprise	Density of neural firing
Weiner and Graham (1984)	happiness, sadness	Attribution independent

Table 2.2: *A list of theories on Basic Emotions, sorted alphabetically by the first author's name. Adapted from [126].*

emotions should be considered to be *basic*. An overview of these theories, sorted alphabetically by the first author's name, is presented in the Table 2.2. The table shows that there are three main ways in which the notion of basic emotions has been used in the literature [177]: evolutionary evolved responses to fundamental survival tasks [52, 4], biologically determined (hard-wired) basic emotions [69, 83, 130], and emotions that are basic in their descriptive terms [137].

Ekman [52] suggests that there are a number of discrete emotions that differ one from another in important ways. For instance, fear, anger, and joy differ in their eliciting conditions, as well as in their usually associated behavioural and physiological characteristics. However, basic emotions, according to Ekman [52] are also characterized by a set of common properties. As such, a basic emotion would be present in non-human species, be triggered rapidly and automatically in response to an event, and appear spontaneously and for a short duration. Furthermore, it has specific trigger conditions. If, according to this approach, emotions are considered to have evolved to respond to fundamental tasks for survival that present a phylogenetic adaptive advantage, then it is logical to believe that there are distinct universal trigger events for basic emotions (e.g. the loss of a loved one would be a universal condition triggering intense sadness).

Izard [83] suggests that these discrete emotions have a biological basis, and they are basic for the organism. They evolved due to their adaptive value in helping organisms deal with recurrent, fundamental life and survival related tasks. Thus, the characteristics shared by these emotions are largely biologically determined [177].

Plutchick [137] argues that these emotions are fundamental and sufficient elements to describe all emotional phenomena. The term *basic* applies to them in the sense that they are descriptive of the most common pan-species emotional phenomena, and when combined, they can produce other more complex emotions [177].

It is important to note that the focus of biological and evolutionary theories does not extend to emotions in sophisticated social relations, as are common for human beings. Social emotions, such as guilt and pride, depend on self-reflection and an understanding of networks of social relations. However, the meaning of sophisticated social emotions in HRI is both unclear and likely to be problematic (see Section 4.8.4).

Dimensional Theories

A different research tradition is a dimensional approach, in which the affect is described in relation to independent elementary dimensions that can be combined.

According to the model proposed by Russell [150], it is possible to represent emotions using a circle in which two axes alone are necessary: the dimension of valence indicating pleasure/displeasure and the arousal dimension (weak/strong), which represent the affect as a subjective experience on a continuum [9], see Figure 2-1. This

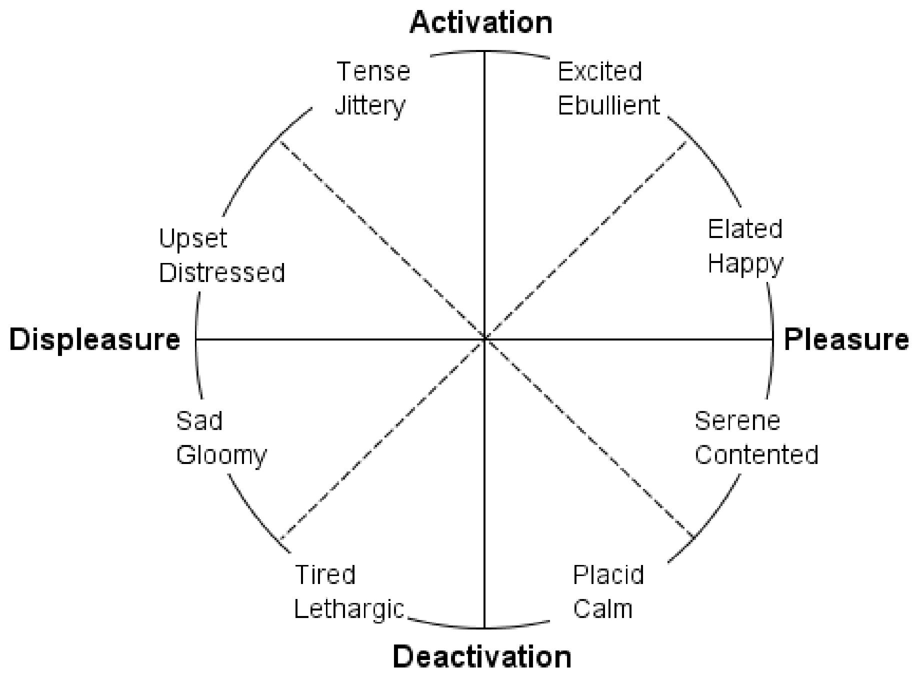


Figure 2-1: *A circumplex model of affect. Adapted from [151].*

circular model is called *circumplex* because it postulates meaningful regions of subspaces within the overall scheme. For example, a high degree of activation coupled with moderate displeasure corresponds to a condition that is tense or jittery. Currently this approach is probably the most commonly used for measuring subjective emotional experience [58]. This representation is found in different cultures and is potentially universal, although this is not always confirmed by empirical data [174]. The two-dimensional models are appealing in that they allow one to graphically illustrate similarities and differences between emotions in terms of neighbourhood in space [156].

However, it is still an open question what number of dimensions is necessary and sufficient to properly represent and differentiate between emotions [133]. For example, fear and anger are found in the same place in the valence-arousal circumplex because both of these emotions are particularly negative and intense. However, on a subjective, expressive and behavioural levels, these two emotions are very different. Thus, emotions are sometimes conceptualized on other psychological models that incorporate three dimensions, such as a model of Pleasure-Arousal-Dominance (PAD) which has been used to research head and body movements [94]. In the PAD model, the Pleasure-Displeasure scale measures how pleasant an emotion is, the Arousal-Nonarousal scale measures the intensity of the emotion, and the Dominance-Submissiveness scale represents the controlling and dominant nature of the emotion [109]. Pleasure and Arousal in this model are equivalents of Valence and Arousal of the previously described Russel's circumplex. Dominance represents the amount of influence an agent feels the environment has upon them and vice versa [127]. More specifically, in a self-reporting context, dominance refers to whether one feels in control or not, whether one feels powerful or not, and whether one feels overwhelmed or not [108, 110]. If one feels dominant, this means one feels in control and/or powerful and/or not overwhelmed and able to influence the environment. If one feels submissive it is the other way around. When rating scales of this kind are used by observers, they denote beliefs about the emotional state of another agent. For example, in the case of dominance, the extent to which an observer believes an observed agent is in control of its actions and environment.

The dimension of Dominance is considered to be a useful factor when modelling synthetic affect or measuring emotions [26]. An immediate value of Dominance in computational modelling of emotion is recognized when considering it as a factor to differentiate between the emotional states of anger and fear. However, some researchers state that affect measurement does benefit from including dominance, and that dominance cannot be discarded as a redundant factor [26]. Whether it should be included is largely a matter that concerns the objective of the researcher. In human-computer interaction, for example, feelings of being in control are fundamental to designing positive user experiences. It is difficult to conceive of a case in HRI where this would not also be true.

Appraisal Theories

An alternative representation of emotion is based on appraisal theory. This theory states that emotions derive from our evaluations/appraisals of events that cause specific reactions in different people. This theory provides more flexibility than discrete and dimensional models, accounting for differences among individuals and different responses to the same stimulus by the same individual at different times. The most frequently implemented model of appraisal is the OCC model [125], where OCC stands for Ortony, Clore, and Collins. The OCC model categorizes 22 emotions based on the positive or negative reactions to events, actions and objects. It states that a given emotional strength/intensity depends primarily on the events, agents, or objects in the environment of the agent exhibiting the emotion. Therefore, OCC requires an account of relevant context in order to derive an interpretation of an agent's state.

2.2.3 Emotional Expressions in Humans and Animals

Emotional expressions are those potentially observable changes in face, voice, body, and activity level. Emotional expressions are seen by some as the manifestations of internal emotional states [54, 99]. Although the relationship between expressions and states remains somewhat vague [101], no single measure of emotional states or action patterns is more differentiating than emotional expressions.

There has been intensive research in the field of emotion recognition using various modalities where the analysis of facial expressions and voice are the most popular techniques. 95% of the literature on human emotions has been dedicated to using face stimuli, majority of the the remaining 5% - on audio-based research [46]. However, there are emerging modalities related to body that have been considered to have a potential value for the recognition of emotions [185]. Furthermore, whereas all robots should have a body, the presence of face is an extra that may not make sense. So bodily movements have special potential in HRI.

Emotion communication through bodily expressions has been a neglected area for much of the emotion research history [46]. Nevertheless, body language and other non-verbal cues play an important role in the process of revealing unspoken intentions and feelings in human communication. Some researchers [19] claim that 93% of a human-human communication is based on non-verbal cues, such as body language and paralinguistic features.

Changes in a person's affective state are reflected by changes in their body posture [71]. To date, the bodily cues that have been more extensively considered for affect recognition are static postural configurations of head, arms, and legs [41, 90], dynamic hand/arm movements [180], head movements using its position and rotation [39], and head gestures such as head nods and shakes [70].

Human recognition of emotions from body movements and postures is still an unresolved area of research in psychology and non-verbal communication [71], although a series of studies has been performed to date investigating the relation between static non-verbal bodily cues and perceived emotional states. In general, recognition of affect from bodily expressions is mainly based on categorical representation of affect. The categories of *fear, happiness, sadness, anger* and *surprise* appear to be more distinctive in bodily motion than categories such as pride and disgust [71]. The emotional expression of *fear* is associated with a backward transfer of a body weight [41], stepping backwards or even moving the whole body backwards [41]. The same attribute of body movements are associated by [41] with the expression of *surprise*. *Fear*, in addition, makes the body contract as an attempt to appear as small as possible, while *joy* may lead to movements of openness and acceleration of forearms upwards [185]. The expression of *anger*, contrary to the expression of *fear*, is associated with a forward transfer of a body weight [41], moving limbs away from body [44], stepping forwards or moving the upper body part forwards [41]. The expression of *joy* is associated with moving limbs away from body [44] and raising head and shoulders [180]. The emotional bodily expression of *sadness* is associated by researchers with moving limbs close to a body and making the body contract [44].

All the described cues are static postural configurations of various positions of heads, arms and legs. An important outcome of the studies is the finding that combinations of expressive characteristics are associated with specific emotions [180, 47]. Therefore, emotional bodily expressions may need to be described by a set of features to uniquely associate an emotion with bodily expressions. In addition, emotional states in real life are expressed not only in a static way, but also using dynamic aspects and abilities of a body. Robots behave dynamically in the environment with types and ranges of movement that are appropriate to their role. Consequently, it is vital to conceive of a scheme for entering and changing a posture, not merely defining a set of static poses without consideration of how they are to be produced.

Movement Quality and Laban Movement Analysis

In general, two approaches can be distinguished to understanding emotional expressions: one approach focuses on movement type, the other on movement quality. The first approach, presented in the previous section 2.2.3, focuses on the way in which movements are executed with respect to the dimensions of space and time.

In the second approach, researchers focus on the qualitative characteristics of movements. They define movement quality descriptors such as speed, smoothness, tension, and force. In the study of dance, this approach is best exemplified by the Laban Movement Analysis (LMA) [93]. Modelled after musical notation systems, it uses symbols to represent the actions or positions of the body. The qualitative aspects of body movement are represented by the general components of Effort and Shape. Effort in LMA describes the inner attitude towards the use of energy along four bipolar components: Space, Weight, Time, and Flow, with their extremes being Indirect/Direct, Light/Strong, Sustained/Sudden, and Free/Bound, respectively [85]. Shape consists of Shape Flow, Directional, and Shaping/Carving, all of which describe dynamic changes in the movement form [85]. Laban Effort and Shape components provide a comprehensive set of descriptors, which seem closely related to emotion as shown in several perception studies [47, 44].

LMA, although initially created as a model to analyse human expressive movements in the study of dance, is now used for other research purposes, such as automatic recognition of emotional expressions in affective computing [44] or in psychological research on human personality [100]. Moreover, LMA has a potential to enhance a research on non-verbal human-robot interaction [114]. LMA is not adequate by itself to describe robotic movements, mostly because robots can vary dramatically in form and expressivity. In this thesis, we define *expressivity* as a property that refers to aspects of the construction of a robot that constrain the robot's ability to perform expressive movements.

2.2.4 The Role of Emotions in Nature

In two previous sections of this Chapter we have presented a brief overview of prior research showing that certain human emotional expressions are consistently recognized by people. Evolutionary psychologists [45, 83, 53] claim that these emotions evolved during evolution to serve certain functions [160]. Darwin (1872) proposed that there are two main classes of such functions:

- Preparing the organism to respond adaptively to environmentally recurrent stimuli, and
- Communicating critical social information.

Subsequent researchers [136, 79] further developed the idea of adaptive response and social communication and provided more detailed lists for each class of functions. Specifically, [79] pointed out the following functions critical for adaptive purposes of human organisms:

- Regulative function. Emotions provide a signal of any abnormal external or internal values perceived. In such a way, they can protect the organism from injuries.
- Selective function. Emotions influence the perception of the environment as well as the perception of internal stimuli.
- Motivational function. Emotions activate and control the behaviour of humans. Humans try to experience comfortable rated emotions more often and avoid uncomfortable emotions.
- Rating function. Emotions can be used to evaluate situations and differentiate between those that are comfortable and uncomfortable.
- Expressive function. Emotional expressions are used to conduct non-verbal information using faces, gestures, body postures and the tone of the voice.

In terms of social communication, [136] specified the following problems directly associated with emotions:

- Territoriality. The basic emotions related to territoriality are exploration and its opposite, surprise (or in other words, control or dyscontrol). They are developed through exploration of the environment.
- Temporality. This allows to take into consideration the limited duration of an individual's life. Distress or sadness signals for social support, nurturing responses

in other members of the social group are also considered. Joy, being an opposite of sadness, is produced to experience a possession or rejoining and signals that everything works well.

Not surprisingly, the functional role of emotions are mostly investigated by psychologists and sociologists. However, researchers of such areas as artificial intelligence and robotics see potential benefits of using artificial emotions in both autonomous robotic agents for responding emotionally to situations experienced in the world [111] and in social robots to communicate successfully with people [129]. It would be a mistake to dissociate the adaptive and the social functions of emotional state: emotions can only be expressed if they have first been generated. Social communication requires to detect the emotional state of a peer and then to make sense of it in terms of their relationship.

2.3 Emotions and Emotional Expressions in Robots

Research on the recognition of emotion in human-human interaction has inspired the creation of artificial emotional expressions in virtual agents [2, 128, 102] and robots [107, 6, 49].

However, it is important to remember that robots do not always have a humanoid or human-like body, thus the direct transfer of human emotional body language to a robot is not always easy or straightforward. Non-humanoid robots form an extremely large class in the whole range of different robotic forms. The map presented in Figure 2-2 shows different robotic embodiments ranging from highly expressive robots towards low expressive ones, to illustrate the importance of non-humanoid forms in the space of possible designs.

Low and semi-expressive non-humanoid robots can be used more often for home-working tasks (e.g. a robotic vacuum cleaner Roomba), search-and-rescue [17], domestic assistance [184] and other tasks. The design of such robots is intended to match their purpose, e.g. designed to move across disaster zones to find and reach victims, or to be steady and move safely in order to help elderly or disabled people get out of bed and move around. Thus it is not always useful or possible for such robots to have human-like bodies. However, as social agents, it is still useful for robots to be able to generate cues that are capable of expressing aspects of their state that are relevant for social coordination. And although most studies on the expression of emotions in robots make use of humanoid robots, it is well known that humans can perceive affective states from non-anthropomorphic demonstrators [86] and even from abstract geometrical shapes [78].

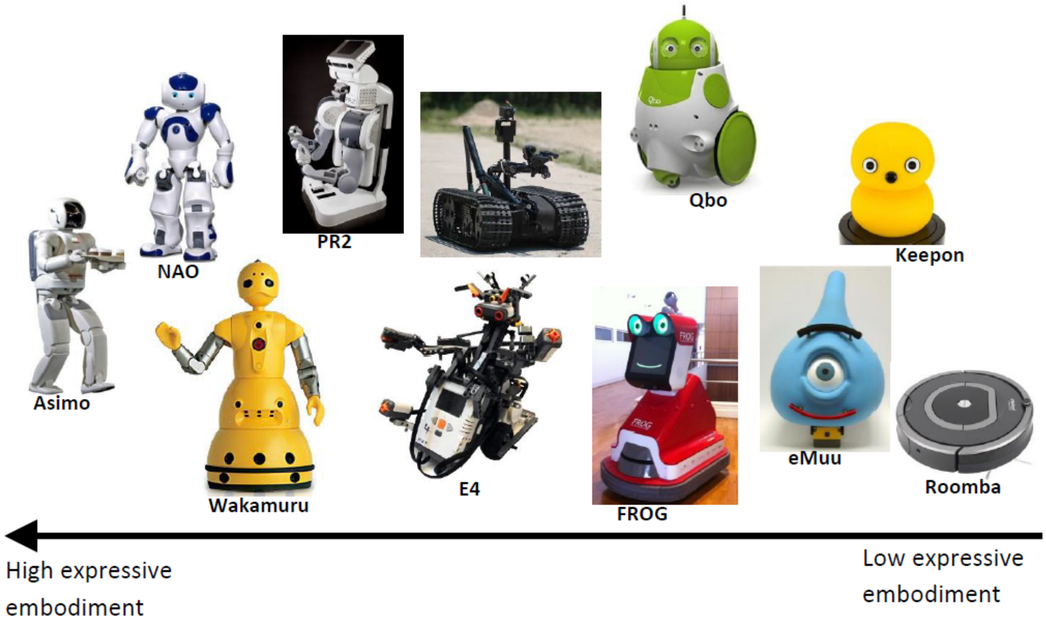


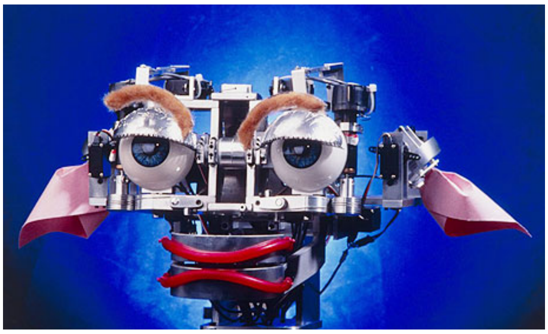
Figure 2-2: *Multitude of robotic embodiments along a dimension of Expressiveness. Robots on the left contain more degrees of freedom available for expressivity.*

2.3.1 Computational Models of Artificial Emotions in HRI

Recent years have seen a significant expansion in research on computational models of human emotional processes, driven both by their potential for basic research on emotion and cognition as well as their promise for an ever increasing range of applications, including autonomous robotics and human-robot interaction.

In general, emotional architectures for robots or virtual agents are based on our understanding of how humans and other species perceive, reason, learn and act upon the world. It is possible to distinguish different types of architectures according to the affective states they try to model (e.g., emotions, moods, personality); the types of processes captured (e.g., appraisal, coping); the integration with other cognitive capabilities; and the expressive power they possess.

One of the first emotional models of robot control developed by [23] used emotional dimensions of arousal, valence, and stance to categorize a set of emotions that were generated as facial expressions of the Kismet robot (Figure 2-3). The computational model of Kismet's emotions represents robot's behaviour as a set of drives with an internal intensity of each. The emotions are triggered by specific antecedent conditions, such as presence of an undesired stimulus, praise or prohibition. The emotional states are categorized using three dimensions of valence, arousal and stance. Stance in this work specifies how approachable the percept is to the robot. Positive values correspond to advance whereas negative values correspond to retreat. The dimension of stance is very research-focused in the work of [23]. However, it is possible to say that this



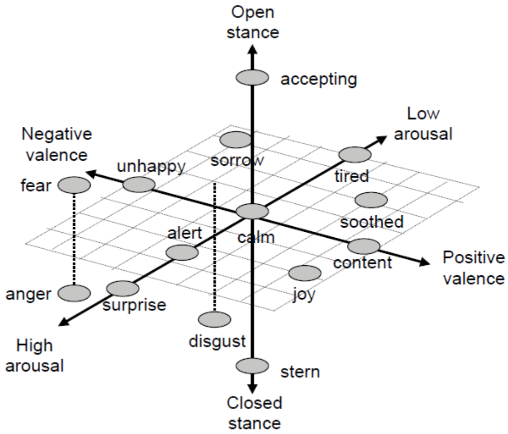


Figure 2-3: *Left: social robot Kismet developed by Breazeal. Right: categorizing emotions in Kismet. Adapted from [23].*

dimension could be generalized to a wider concept of dominance, so that the situation when an object is easily approachable by a robot corresponds to a high dominance and vice versa.

Another computational model of emotion, used to develop the social robot Probo [154] (Figure 2-4), uses two dimensions of valence and arousal to construct an emotion space, based on the circumplex model of affect defined by Russell [150]. In the emotion space a Cartesian coordinate system is used, where the x coordinate represents the valence and the y-coordinate the arousal, consequently each emotion e (v, a) corresponds to a point in the valence-arousal plane (Figure 2-4 right). This way, the basic emotions can be specified on a unit circle, placing the neutral emotion e (0, 0) in the origin of the coordinate system. Thus, each emotion can also be represented as a vector with the origin of the coordinate system as initial point and the corresponding valence-arousal values as the terminal point. The direction α of each vector defines the specific emotion, whereas the magnitude defines the intensity of the emotion. The intensity i can vary from 0 to 1, interpolating the existing emotion i = 1 with the neutral emotion i = 0. Each Degree Of Freedom (DOF) that influences the facial expression of Probo is related to the current angle α of the emotion vector. Probo, the same as Kismet, is a robot that expresses emotions using only its face. Moreover, it lacks an underlying model of emotional state to drive the coordinate system of pleasure and activation. It is important to create a convincing system that integrates the trigger against a background cognitive process, appraising events to generate an external emotional representation.

There also exist emotion architectures for robots that use the process of appraising the situation in their computational model. For example, in the iCat chess player [97], a robot that provides affective feedback to the user, emotions result from affective signals that emerge from an anticipatory system containing a predictive model of itself and/or of its environment. This anticipatory system generates an affective signal resulting from

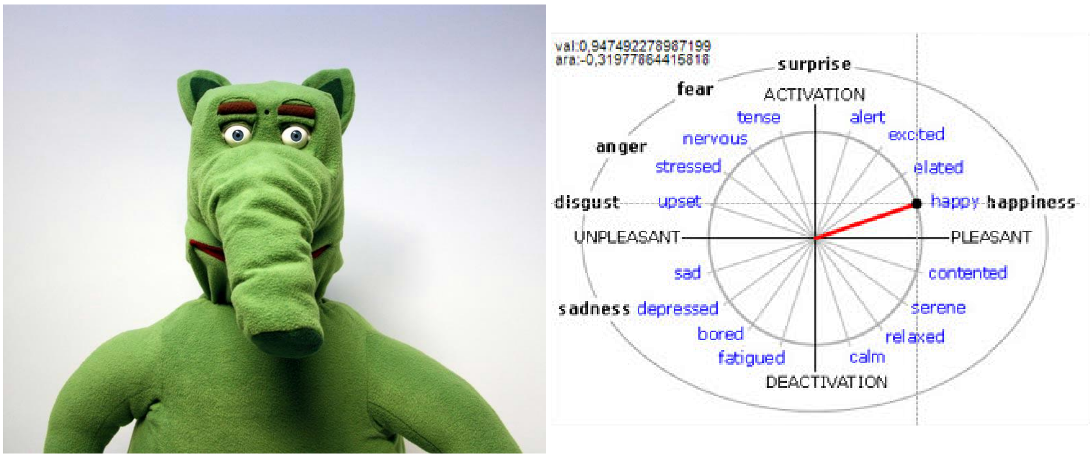


Figure 2-4: *Left: social robot Probo. Right: emotional dimensions in Probo. Adapted from [154].*

the mismatch between what is expected and what the robot senses. If the robot expects the user to perform well in the game and the user makes a mistake, it is an unexpected and positive situation for the robot, leading to the generation of a positive valence affective signal and an associated positive facial expression (Figure 2-5). In addition to commonly used emotional states described with a help of emotional dimensions, such as valence, iCat's model additionally uses an affective state of mood. Mood works like a background affective state, when other emotions are not occurring.

To summarise, the majority of computational emotional models, used to control social robots, include some discrete emotional states. These discrete emotions are usually mapped on a space of two or more emotional dimensions, where valence and arousal are the most popular ones. Discrete emotions are usually triggered by some changes in the robot's environment and then generate specific responses that are transferred to specific facial expressions of a robot.

We see several limitations in the existing models. One of the limitations is a lack of interaction between either the emotional states or emotional dimensions. In real life, people often experience several different emotions at the same time, feeling some of them more and others less strongly. It is important for a computational robot control model to include a mechanism that would be able to swap between emotional states properly or interrupt the current emotional behaviour if necessary. Another limitation of the discussed models is that all of them execute the actions associated with a specific emotional state immediately after the trigger was activated. We believe there should be a time gap between an emotional activation and an execution of the specified behaviour. Such a time gap can provides additional useful information to a robot's observer about the potential intention of a robot. Finally, the current computational models of robot emotions do not use the emotional dimension of Dominance and thus miss some important information (the value of Dominance was discussed in

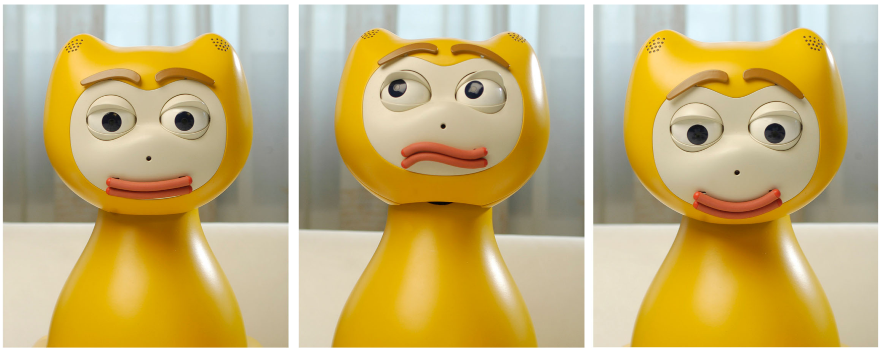


Figure 2-5: *Social robot iCat.*

Section 2.2.2).

2.3.2 Emotional Expressions of Robots in HRI

There is a growing body of research on techniques for expressing artificial emotions via facial expression, in both human-like and non-humanoid robots. The work of [36] explored interaction with the Lego-based 70cm-tall 'humanoid' Feelix robot through tactile stimulation so that various kinds of stimulation elicited the robot's emotional responses. Observation of spontaneous interactions with Feelix showed that humans anthropomorphize a lot when interacting with objects with human-like features, so only a few of human-like emotion-related features are needed to make the interaction believable.

Eddie [169] is another low-cost emotional robot developed in Germany. The 23 degrees of freedom (DoF) and actuators assigned to particular action units of the facial action coding system allow it to express emotions using eyes, eyebrows, ears, mouth and jaw, and the crown. This robot uses animal-like features (crown of a cockatoo and ears of a dragon lizard) to display basic human emotions, which are recognized well by users.

Emotional expressions of a non-humanoid robot are presented in the work of [154] with a huggable animal-like robot Probo, shown in Figure 2-4. Probo has a fully actuated head, with 20 degrees of freedom, capable of showing facial expressions and making eye contact. The Probo robot is focused on interaction with hospitalized children.

It is perhaps unsurprising that the majority of prior work on emotional signalling focuses on facial expression. People typically identify sadness, for example, with a frown. However, the influence of affective states in humans and in animals is experienced throughout the whole biological system. Sadness may also be accompanied by lowering of shoulders, slumping, a reduced pulse and slowing of bodily movements. As we shall discuss next, faces may not always be appropriate for robots.

2.3.3 Emotional Body Language in Robots

Non-verbal communication through body movements plays an important role in human communication. Expressing emotions is one of the main functions of bodily communication [3]. But people and animals do not only *express* emotional feelings, they also *communicate* certain information through their emotional postures and gestures. That is, expressions can be directed at peers or co-workers for the benefit of their mutual understanding. Thus expressive behaviours can serve as a rich source of information in inter human communication.

Heider and Simmel [78] demonstrated in 1944 already that people are biased to interpret moving figures and motion patterns in social or emotional terms. Their experiment showed that it is possible to communicate contextual or even emotional meaning to people through very basic forms and thus created the base for future work on emotionally expressive robots.

As we have already discussed in Section 2.2.3, there exists scepticism among researchers about the ability to reliably identify emotions from the body. The scepticism has its roots in very early empirical results [51]. So why use bodies and not faces for expressing emotions in robots? Reasons could be numerous [46] based both on a human psychology research and on the specifics of a robotics area.

1. First of all, in spite of the scepticism of recent decades, a number of behavioural experiments showed that recognition performance for bodily expressions is very similar for face and body stimuli [41].

2. Second, a major difference between facial and bodily expressions is that the latter can be recognized from a much greater distance [179]. This potentially influences the communicative role of facial and bodily expressions, as for example facial expressions could give more information on an internal state of a person while bodily expressions direct attention to a person's actions.

3. Some emotions are more powerfully expressed and easier conveyed using a body than using a face [5]. Some previous studies showed that e.g. when viewing aggressive body pictures, observers spend the most of time looking at hands not faces [85].

4. Finally, it is not clear that robots could or even should have expressive human-like faces. Low and semi-expressive non-humanoid robots can be used more often for home-working tasks (e.g. a robotic vacuum cleaner Roomba), search-and-rescue [17], domestic assistance [184] and other tasks. The design of such robots is intended to match their purpose, e.g. designed to move across disaster zones to find and reach victims, or to be steady and move safely in order to help elderly or disabled people get out of bed and move around. Thus it is not always useful

or possible for such robots to have human-like faces. However, it is still useful for them to be able to show expressive cues, as it is a fundamental social signal.

For designing expressive and communicative robot movements it is important to know which features cause the interpretation of intentions and emotions [63]. To date, research has mostly focused on the identification of features related to animacy [157]. However, there exist a small number of studies investigating the relation between robot movements and perceived emotion. The biggest part of these studies use humanoid robots as examples and almost directly transfer human emotive gestures to humanoid robot bodies [14, 183].

Bodily expression can be generated by directly simulating human static postures and movements as done in, e.g., [186], [15]. A more generic approach for generating expressive behaviours, however, is to modify the appearance of a behaviour via the modulation of parameters, such as speed and scale, associated with that behaviour. Wallbott [180] investigated whether body movements, body posture, gestures, or the quantity and quality of movement in general allow us to differentiate between emotions. This study found that qualities of movement (movement activity, spatial extension, and movement dynamics) and other features of body motion can indicate both the quality of an emotion as well as its intensity. Laban movement analysis (LMA) [93] models body movements using four major components: body, space, effort, and shape, characterized by a broad range of parameters. Based on LMA, Chi et al. [38] developed the EMOTE framework that uses post-processing of pre-generated behaviours to generate expressive gestures for virtual agents. The model developed by Pelachaud et al. [132] modifies gestures before generating actual movements. This model distinguishes spatial, temporal, fluidity, power, overall activation, and repetition aspects of behaviour. It has been applied to the GRETA virtual agent [105] and the NAO humanoid robot [96] for communicating intentions and emotions. These methods can be applied to functional behaviours in order to express affect in a robot while it is performing a task.

Karg et al. [86] analysed if a hexapod robot can express emotion in the way it walks and if these expressions are recognizable. The authors mapped human emotive gait parameters to a hexapod by changing a step length, height and time for one step depending on the emotion. The results of the study revealed that different levels of pleasure, arousal and dominance were recognizable in the way the hexapod walked. Furthermore, higher velocity of a gait resulted in a higher level of perceived arousal, while lower velocity resulted in lower pleasure and lower dominance.

Saerbeck and Bartneck [153] also analysed the relationship between the motion characteristics of a robot and perceived affect. They systematically varied two motion characteristics, acceleration and curvature, and found a strong relation between these parameters and attribution of affect, e.g. they found that the level of acceleration is correlated with perceived arousal. They did not find a direct relationship between acceleration or curvature and perceived valence. Two robotic embodiments - the iCat robot shaped as a cat with an animated mechanical face and the Roomba robot of a circular shape - were used in this experiment. The authors did not find significant differences between the embodiments, thus suggesting that motion design tools can be used across embodiments.

In a recent study, [166] investigated how a dog-inspired tail interface can be applied to utility robots and communicate high-level robotic states through affect. The study indicated that people were able to interpret a range of affective states from various tail configurations and gestures. As a result, the authors presented a set of guidelines for mapping tail parameters to intended perceived robotic state, e.g. a higher speed projects a higher valence and arousal while a lower speed projects a lower valence and lower arousal, a large horizontal wag results in a higher valence.

It is common for non-humanoid robots to vary greatly in the number of embodied degrees of freedom, and the maximum amplitude, velocity and frequency of motions they are able to perform. This means they vary in their capacity for expressive behaviour or *expressivity* as it is treated in this thesis. However, there are some similarities in the influence of the parameter on perceived dimensions of emotional meaning, e.g. higher speed of expressive movement often increases perceived level of arousal, or that reduction of size can reduce the perceived level of dominance. Thus, it may be that all robots are capable of expressing basic emotional states, regardless of their form factor, as long as their behavioural capabilities are mobilised appropriately. However, this is still an open question in robotics and represents a central concern of this thesis.

2.4 Role of Emotions in Robots

Emotional expressions of robots have many positive impacts on human–robot interactions including the following aspects: the way of interacting with a robot, the attitude towards a robot, the effectiveness of joint tasks.

Emotional interactions play different roles and have various purposes in the context of HRI. Among others, we can distinguish the following:

- The illusion of life. The design of adaptive emotional behaviour must use particular caution to avoid unexpected or unintelligible behaviour. This problem can be solved by following a number of guidelines on the methods for creating expressive behaviour in robots, which provide the robots with the "illusion of life" [143]. This illusion will lead to the user's "suspension of disbelief", which increases the perception of social presence, thus rendering the robot as a believable character [13].
- Improved engagement and more efficient behaviour with robots. Emotions contribute to engagement in a social interaction context. Engagement, in this con-

text, is defined as "the process by which two (or more) participants establish, maintain and end their perceived connection" [164] and has received ever increasing attention by the HRI community [144].

- Improved attitude towards an emotional robot. The lack of adaptive emotional behaviour decreases the user's perception of social presence, especially during long-term interactions [98], which in turn renders the robots to be non-believable characters [13]. To be perceived as socially present, social robots must not only convey believable affective expressions, but also be able to do so in an intelligent and personalised manner, for example, by gradually adapting their affective behaviour to the particular needs and/or preferences of the users.

2.4.1 People's Attitude towards Robots

Although computers are not similar to people at all, several studies have suggested that we treat computers as social actors [142]. Thus we could make an assumption that it is possible we may treat artificially synthesized emotional expressions as real emotional expressions. In fact, several studies suggest that this is indeed the case, including [22, 18, 103], who all found that a computer agent which was empathetic toward the user (through the use of facial expressions and textual content) was generally rated more positively by subjects when compared with an agent which was not empathetic toward them.

Emotional behaviours made elderly participants perceive a robot as more empathic during their conversation [30]. Emotional gestures improved participants' perception of expressivity of a NAO robot during a story-telling scenario [31]. In another study [33], this robot responded empathetically to children's affective states. Results suggested that the robot's empathic behaviours enhanced children's attitude towards the robot.

Most of these studies use humanoid robots as social actors, so there is a gap in the literature analysing people's attitude towards non-humanoid robots. Moreover, it is usually difficult to compare the results of various studies as each of them use a different tool for evaluating people's attitudes, depending on the attitudes that concern the researchers.

There exists a standard validated measurement instrument, called the Godspeed Questionnaire Series [12], for evaluating how people perceive the robot according to five HRI concepts: anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety. It uses for each concept several semantic variables graded from 1 to 5. The Anthropomorphism concept describes the attribution of human-like features and behaviour to non-human things (variables: naturalness, consciousness, life, elegant movements). The Animacy represents the concept of being alive (variables: alive, lively, organic, lifelike, interactive, and responsive). The Likeability depicts the positive impression about others people might have (variables: like, friendly, kind, pleasant, nice).

The Perceived Intelligence represents the expected capabilities the robot has (variables: competent, knowledgeable, responsible, intelligent and sensible). The Perceived Safety illustrates the comfort level the people might have with the robot (variables: relaxed, calm and quiescent). These five HRI concepts have an uncertain relationship with the more fundamental matter of emotional state.

There are many HRI studies that use this tool to evaluate robots in different interactive situations and tasks [172, 11, 176, 50, 92]. Only few of them use the tool for evaluating how people perceive emotionally expressive robots. For instance, [50] study the effects of emotional gaits from the biped humanoid robot WABIAN-2R on the subjects' perception of the robot in terms of animacy, likeability, anthropomorphism, perceived intelligence and perceived safety. Another recent study [92] utilized an emotionally expressive robot head to evaluate people's attitude towards it. Giuliani et al [65] compared task-based and socially intelligent behaviour of a cat-like robot bartender, that used facial expression of its face to enrich its social behaviour.

However, all these studies were either focused on humanoid robots or used only facial expression of emotions in the robots. Thus there is a gap in the literature for the attitude towards non-humanoid robots using emotionally expressive body language.

2.4.2 Predictability of Robots in Human-Robot Teams

Robots are used as interactive systems in human-robot teams. People tend to treat all interactive systems as if they are social agents [142]. When treated as social agents, interactive systems are additionally attributed with social qualities, such as helpfulness or obstinacy, which can influence a person's readiness or ability to make use of them. If these qualities are appropriately ascribed to interactive systems, they promise to facilitate social coordination. From a design perspective, this depends upon creating situationally appropriate cues that can effectively encode relevant social qualities. Moreover, this predictability should be beneficial for a robot in a human-agent team in order to satisfy the definition of collaboration. Further research in HRI is needed to provide experimental evidence of whether predictability of robots is improved when they are designed to use non-verbal emotional cues for interaction with people.

2.4.3 People's Behaviour with Embodied Artificial Agents

A long-term field study showed that facial expression of robot mood influenced the way and the amount of time that people interact with a robot [29]. Several studies also reported effects of affective virtual agents on performance. In Klein's study [40], participants who interacted with the affective support agent played the game significantly longer. Maldonado et al. [43] found that participants who interacted with the emotional agent performed better in a test in a language learning context. Berry et al. [44] studied the effects of the consistency between emotion expressions and persuasive messages about healthy diet using the GRETA virtual agent. Results showed that GRETA with consistent emotion expression resulted in better performance of memory recall. Emotion expression was reported to have effects on users' affective states and behaviours. All these studies suggested that emotional expressions of virtual agents have effects on the users during interaction. However, there is still a gap in the literature on what is the effect of the artificial emotions in physically embodied robotic agents, especially those interacting with people on some joint tasks.

2.5 Summary and Discussions

In this Chapter, we present the concept of emotion and provide a formal definition of the term for use in HRI research. We review the existing literature on psychological theories of emotion, preparing a base for linking natural emotions to artificially synthesized ones. Later we provide a deeper background regarding emotional body language as it appears in humans, introducing the state of the art research on emotionally expressive body movements in humanoid and non-humanoid robots. Finally, we review prior work on people's attitudes towards social robots as these are likely to play a role in determining the effectiveness of robot bodily expressions in interactions with humans.

There is a growing body of HRI research on techniques for modelling emotional states and expressing artificial emotions in robots. However, this research has several limitations. First of all, the existing computational models of emotions used in social robots lack the mechanism for arbitration and interruption of a specific emotional action. In addition, these models do not usually use a dimension of Dominance and do not allow for the time course between triggering an emotional state and executing a corresponding emotional reaction. Furthermore, the majority of prior research has focused on techniques for expressing emotions in robots via facial expressions, ignoring the potentially more far-reaching value of bodily movements for robots to signal and communicate emotional information. Another limitation of the previous HRI research in artificial robotic emotions, which is closely related to the first one, is that the majority of prior studies are focused on the humanoid robots only and do not consider other non-humanoid robotic forms. There is a considerable gap in the current literature between high-level design guidelines for bodily expression of robotic emotion and the implementation of a specific robot with expressive movements. Finally, it is still an open question in the HRI research what is the value of robot emotions in the interaction between people and robots, and especially in human-robot collaboration.

This thesis addresses challenges in modelling the affective condition of an artificial agent so that it is possible for a robot of arbitrary form to express its emotional state systematically in a manner that a human collaborator can reliably interpret. In the next chapter we give an overview of a methodological approach and some techniques used to inform the research for this thesis. We will overview three commonly used approaches to presenting emotional expressions of robots to observers, give a description of the robotic platforms used in our studies and present our tool of choice for measuring emotional perception.

CHAPTER 3

METHOD

3.1 Introduction

In this chapter, we present a review of the experimental tools that have been used in the research presented throughout this thesis with respect to the four research questions to be addressed. Specifically, we overview four commonly used approaches to presenting emotional expressions of robots to observers: using physical robots, video recordings, robotic simulations and a Wizard of Oz technique. Based on the discussed advantages of each method, two approaches are selected to be used in the studies addressing this thesis: real world observations of a robot and video recordings of a robot behaviours. Then we describe two robotic platforms used in this work: a non-humanoid physical robot E4 and a non-humanoid physical robot Sphero. Finally, following a brief description and discussion regarding the two main schools of thought regarding representations of emotional categories and emotional dimensions, issues surrounding the measurement of emotion and tools developed to do this are presented. This chapter ends with a detailed description of the affective measuring tool of choice, the Self Assessment Manikin, and how it is used in this work.

3.2 Approaches to Presenting Emotional Expressions

The researchers in robotics and HRI do not have a unified opinion towards the use of real physical robots, video recordings of the robots, simulated robotic agents and Wizard of Oz (WoZ) method in experimental studies. The use of a specific approach is often motivated by the research question to address and the specifics of the study. We will present the brief overview of each approach in this section and will discuss the benefits and limitations of each. It is out of the scope of this thesis to compare the effectiveness and usefulness of physical robots vs video-recorded or simulated ones. We use different methods in the different studies throughout our work in such a way that allows us to benefit from the advantages of the specific approach and avoid as much as possible the disadvantages and limitations of the selected method.

3.2.1 Real World Observations

The role of embodiment within social robot interactions with people was questioned several times in HRI research, as a good understanding of the social implications of embodiment clearly informs design of social robots. There are domains where physical interaction between robots and people is unavoidable, such as transportation of things etc. Only real physical robots are suitable for experiments aiming to investigate people's behaviour while interacting with robots in such domains. However, there are other domains where social interaction between robots and people is possible and highly desirable. These are the domains where robots take the role of a servant, caregiver, health advisor, or companion.

Although, as it will be mentioned in the next two subsections, there exist a lot of dispute regarding the use of video recordings of robots, simulated robot avatars and teleoperated robots, the majority of researchers agree that HRI studies with real physical robots are either more advantageous for the human subjects in a variety of ways or at least not less advantageous than virtual and teleoperated robots. According to the literature, the real robots improve the sense of social presence [77], enjoyment and entertainment. It is a widely accepted fact that a robot's physical presence affects human judgements of the robot as a social partner.

The improved sense of social presence, enjoyment and entertainment are the reasons why we have used real world observations of a robot in the study presented in Chapter 4.

3.2.2 Video Recordings

For several studies discussed in this thesis we used video recordings instead of real robot observations in order to overcome the limitations of live trials. The method of using a real robot has several important limitations:

- The beginning and end times of an interaction trial are not clearly defined.
- The context is not clearly defined.
- And finally, while using a real robot its movements are not exactly the same from trial to trial due to the noise in motor accuracy.

Thus, live HRI trials would make it very difficult to control the conditions and to ensure that statistically valid results are obtained. Videotaped HRI trials, on the other hand, overcome these limitations: the movements of the robot are observed as exactly the same by each participant, there is no ambiguity about the duration of interaction, its beginning and end. There is also no ambiguity about the presented situational context in which the robot operates. Woods et al. verified in their study [182] whether videotaped HRI trials for various scenarios could be used in certain situations instead of live HRI trials and concluded that for certain HRI scenarios including the issues of speed, space and distance videotaped trials are representative and realistic, and do have potential as a technique for prototyping, testing and developing HRI scenarios and methodologies. These are the issues that play a crucial role in the context of robot affective expressions, thus the conclusions of the Woods et al. study [182] justify the choice of videos over the real robot for several of our studies.

We have used video recordings of a robot in the studies presented in Chapter 6, Chapter 7 and Chapter 8. In chapters 6 and 8, we present two experimental studies with participants rating an implementation of several expressive behaviours on two non-humanoid robotic platforms. For the purpose of these studies, it is important to make robots' observed movements exactly the same for each participant and to eliminate any ambiguity about the beginning and the end of each robot behaviour. This is why the method of video recordings is an optimal choice for these studies. Chapter 7 focuses on the interaction between situational context and emotional body language in robots. For the purpose of this study it is important to clearly define the context, which is achieved by using the method of video recordings.

3.2.3 Wizard-of-Oz

One commonly employed technique in HRI research is the Wizard-of-Oz (WoZ) technique [87]. WoZ refers to a person, usually the experimenter or a confederate, remotely operating a robot, controlling its movement, navigation, speech, gestures, etc. [146]

Researchers who employ WoZ argue that because robots are not sufficiently advanced to interact autonomously with people in socially-appropriate or physically-safe ways, this method allows participants to envision what future interaction could be like. However, some researchers have raised methodological concerns regarding the use of this technique. For social interaction, Weiss [181] suggests that a WoZ controlled robot is serving more as a proxy for a human and less as an independent entity. Thus, it is not really human-robot interaction so much as human-human interaction via a robot.

Others have raised ethical concerns about the use of WoZ and social deception. Fraser and Gilbert [60] discusses participant gullibility, and subsequent embarrassment, over finding out they have been deceived. They discuss ethical conundrums faced by the experimenter in terms of how to mitigate the necessity of deceiving a participant to keep the simulation realistic against the act of deception. Other researchers [147, 112] also suggest ethical problems when participants cannot tell with whom or what they are interacting - a particular human, a human masquerading as another human, or a machine.

In our work, the main objective is to address the problem of enabling humans to better understand machines. The use of Woz would weaken the results of our studies and could introduce additional ethical constraints. Due to these reasons, the Woz technique has not been used in our work.

3.2.4 Human-Robot Interaction in a Simulated Environment

There is an ongoing discussion on the subject whether using computer simulations in human-robot interaction research is acceptable or not. Many researchers state that simulated environment is too limited for studying interaction between people and robots. For example, [88] reported that individuals felt more engaged during a block stacking task when their counterpart was a robot than when it was a virtual character. Moreover, [138] also detected a higher degree of engagement when participants had a health interview with a robot compared to a virtual character. Besides engagement measures, robots and virtual characters have been compared with respect to other factors such as entertainment. Pereira et al. [134] observed that individuals felt more entertained during a game of chess with the iCat robot than with a virtual version of the robot.

However, other findings are less conclusive: the study with the monocular robot eMuu [10] found no differences with regard to how entertaining participants evaluated the interaction to be. In addition, in another study reported by [88], where participants interacted with a robot or its simulation in either a desert survival task or a teaching task scenario, it was found that the evaluation (in terms of informativeness, reliability, and trust) did not significantly differ between the experimental conditions. The recent study of [80] compared a physically embodied robot with a virtual representation of this robot in a task-oriented or a persuasive–conversational scenario. The results revealed that participants perceived the robot as more competent than the virtual character in the task-oriented scenario, but the opposite was true for the persuasive-conversational scenario. No statistically significant differences between the experimental conditions emerged with respect to objective measures, such as persuasion and task performance.

Although simulated settings cannot substitute for the genuine interaction with a real robot, they can provide useful complementary approaches to experimental research in social human-robot interaction. HRI is an excellent candidate for simulator-based research because of the relative simplicity of the systems being modelled, the behavioural fidelity possible with current physics engines, and the capability of modern graphics cards to approximate camera video. Many of the HRI studies recently reported have relied on simulation, e.g. [37, 145, 124]. The simulators have many inevitable advantages comparing to the real physical robots when used for HRI research:

- Simulated robots do not have problems with batteries, dropped leads, and misaligned sensors.

- The cost of a simulated robot and HRI study, both financial and time related, is significantly lower when using a simulation.
- It is possible to run experiments in parallel with many participants.
- Simulator accurately reflects the range of available information, behaviour, and user experience controlled by the program.

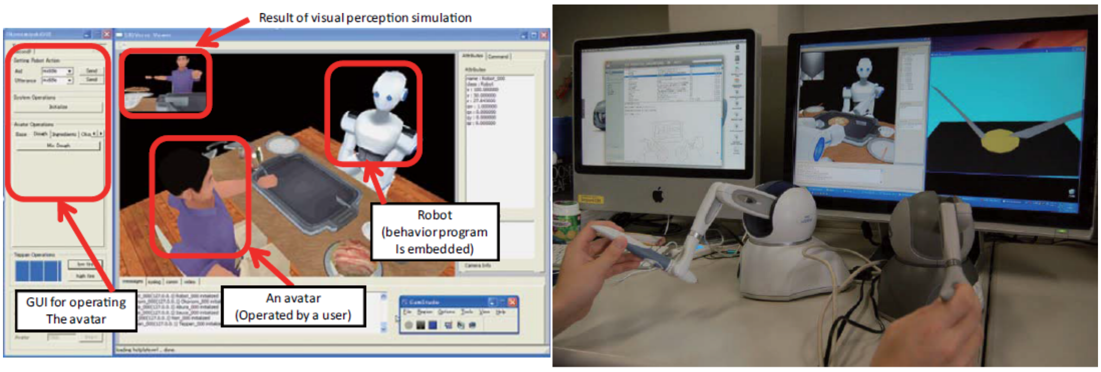


Figure 3-1: *Left: SIGVerse simulator's viewer showing the process of a collaborative task between a person and a simulated robot. Right: A haptic interface used in the HRI scenario in SIGVerse.*

The critical feature for HRI-oriented simulation is that it accurately reflects the range of available information, behaviour, and user experience encountered in actual robot operation. The enhanced human-robot interaction simulator SIGVerse [81] is a good example of such a simulator that enables users to join the virtual world occupied by simulated robots through an immersive user interface. The simulator SIGVerse has a capability to facilitate HRI scenarios making advantage of the following characteristics:

- Robot design: This is a general development platform that offers physics simulation, realistic perception and robot modelling.
- Communication: Verbal and non-verbal communication is available in the simulator.
- Multi-agent and multi-user: Social interaction that involves both multi-agent and multi-user capabilities is available in the simulator.
- Human-agent interface: SIGVerse has a highly customized interface to suit application's needs.

The left part of Figure 3-1 presents a screenshot of a collaborative HRI task as it is displayed on the computer's screen. Here, the simulator's viewer shows the avatar of the person operated by a human user and an avatar of a robot controlled by a behavioural program. It has a graphical user interface for operating the avatar and a window showing the result of robot's visual perception. The right part of the Figure 3-1 presents the capability of the simulator to use a haptic interface during a human-robot interaction task.

The use of simulators as an environment for a collaborative human-robot interaction study is a promising technique because of the following major reasons: lower time related and financial cost, absence of problems with batteries and sensors, and the ease to run experiments with participants. However, collaborative human-robot interaction exceeds the scope of this thesis, this is why we do not use the simulator in our work.

3.3 The Robots

We have used two different robotic platforms in our studies, both of them were real physical robots. In this section we describe each platform in more details.

3.3.1 Physical Robot E4

The robot named *E4* we have been experimenting with is shown in Figure 3-2. It was implemented using Lego Mindstorms NXT and was based on a Phobot robot design [43].

Figure 3-2: *Lego robot E4 used in the studies.*

It includes a head element, with articulated 'eyebrows', that is mounted on a 'neck' element, and two limbs ('hands') attached to its control module. The robot was equipped with three motors that allowed it:

- to move forwards and/or backwards on a flat surface, and

- to move its upper body part. The upper body part was constructed in such a way that the robot's hands were connected and moved together with the robot's neck and eyebrows.

The robot's neck section could move forward and backwards, its hands could move up and down, and its eyebrows could also rise and fall. Figure 3-3 presents three design sketches to illustrate the range of movement available for presenting emotional signals [119].

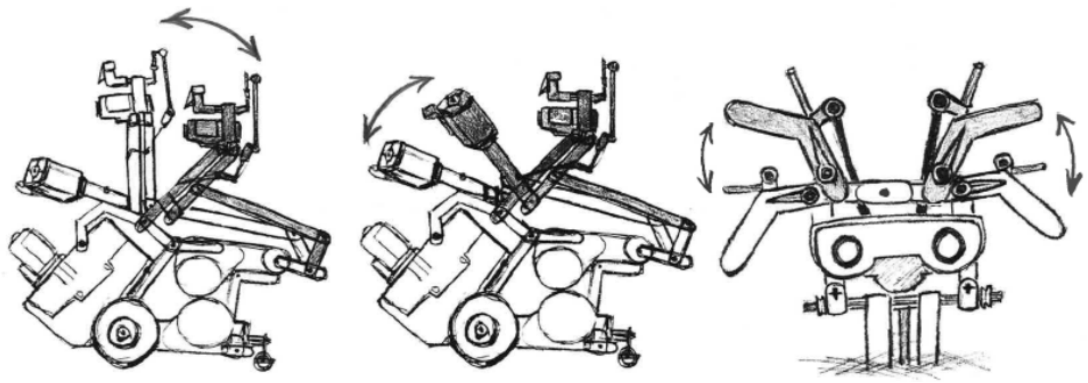


Figure 3-3: *A sketch of Lego robot's expressive movements (left - neck, middle - hands, right - eyebrows).*

For programming robot's behaviours the RWTH – Mindstorms NXT Toolbox for MATLAB [123] was used. This software is a free open source product and is subject to GPL. The RWTH toolbox was developed to control Lego Mindstorms NXT robots with Matlab via a wireless Bluetooth connection or via USB.

3.3.2 Physical Robot Sphero

As the name suggests, Sphero is a robot of spherical shape of the size of a baseball, as shown in Figure 3-4.

It can be wirelessly controlled using smartphone applications. It is a commercial Product by Orbotix [1]. Although contained in a very durable polycarbonate spherical shell, it is not omnidirectional. When sending a drive command into a certain direction, it often has to reorient first before it can drive off. This reorientation is however relatively fast and comes with nearly no lateral displacement. Generally Sphero is very agile and it can achieve speeds up to 2 m/s which is already a quick walking pace. The battery lasts for about one hour and can be recharged using an inductive charging unit which allows the hull to remain without any gateways. According to the development team, the greatest difficulties were fabricating a perfectly round shell which is at the

[1] http://www.sphero.com/contact

Figure 3-4: *Sphero 2.0 robot used in the studies.*

Figure 3-5: *Sphero 2.0 robot's internal configuration. Adapted from [56].*

same time lightweight and strong. They seem to have overcome this issue very well, the shell is even strong enough to withstand an adult person standing on it.

Internally, Sphero uses the concept of a moving cart with a sprung central member [56]. This can be seen in Figure 3-6. All relevant components are packed together and contribute to the mass of the robot. This includes for instance the two motors, battery, computation and communication unit and sensors. Sphero has a three axis accelerometer and a gyroscope to sense movement. Two small wheels with rubber tyres roll along the inside of the shell and can be controlled independently. The normal contact force is provided by an arm that is extending in the opposite direction and slides (slip bearing) against the inner shell, as shown in the Figure 3-6. This way, the wheels never lose contact even in positions where most mass is above the geometric centre of the ball.

3.4 Measuring Perceived Emotions

Much of the work presented for this thesis is concerned with identifying how a robot's body movements are able to convey emotions to people. As such, it is important to outline the approach that has been adopted to facilitate the capture subjects' emotional interpretations, as there are many ways through which this can be done. For this purpose, this section gives a brief overview of the two schools of thought that surround how emotions may be represented. This is followed by an overview of a collection of measuring tools that were considered for use in this research, with a discussion regarding their pros and cons. Finally, the measuring tool that has been adopted - the Self Assessment Manikin - is described in more details, as the underlying design of the tool has impacts upon how the results of experiments presented in the later chapters have been performed and presented.

3.4.1 Representation of Emotion

When it comes to representing emotions or emotional states in artificial systems/agents, there are generally two schools of thought that have been informed by the various theories on emotions: discrete categorical labels, and continuous dimensional emotion spaces. The first school is inspired by the previously discussed Categorical theories of emotion and the theory of Basic emotions (for more details see Chapter 2, section 2.2.2). The second school is inspired by the Dimensional theories of emotion (see Chapter 2, section 2.2.2).

Categorical Labels

Categorical labels, such as "excited", "angry", "sad" or "surprised", are the most familiar way in which people relate and refer to different emotional states, mostly because they are used in everyday natural language. These labels are self-evident, assumed to have a coherent understanding between people and are thus the easiest ways in which to describe different emotions and states [42], and reflect the natural tendency for people to discretise their sensory input from the surrounding world into manageable chunks [84].

Measuring emotion from humans and representing emotions in affective systems have a number of drawbacks and benefits. There is the issue of the number of labels that is to be used during measurement. If there are only a few labels, which has been a common practice in a number of fields, the rating can become more a classification or discrimination task rather than an identification task, so subjects are more likely to provide ratings based on what the expression is not, rather than focusing on what it is, as Banse and Scherer [7] have highlighted. This can be overcome by introducing many more emotional labels [158], however this can make the experimental process longer and the analysis more complicated. On the positive side, this lets assess how many different emotional labels can be broken down into more fundamental underlying emotional dimensions, as demonstrated by Russell with the Circumplex model of emotions [150].

With respect to their representation in artificial systems, the benefit of emotional labels is that each modelled emotional state can have an activation level, which allows multiple emotional categories to be active at the same time. This proved to be useful in the design of systems that recognises and represent multiple complex mental states from the human face [55], and this has been used in our research presented in this thesis for developing an underlying model of emotionally-based robot control.

Dimensional Emotional Spaces

Dimensional representations seek to identify ways in which emotional/affective states may be represented in continuous manner in spaces that have a small number of dimensions. This approach is appealing to fields concerned with creating synthetic systems that deal with emotions, such as Affective Computing [135] and HRI [23]. One of the main attractions of this approach is that dimensions provide a way in which emotional states can be described in a more controllable manner, but can also be translated into and out of common verbal descriptions commonly used by people [59]. This translation is possible as emotion related words can be mapped to different emotional dimensions [150], and thus refer to specific locations within these dimensions [42]. Thus, dimensions are able to not only capture subtle differences in emotion, but it is also possible to interpret the dimensions into more coarse regions which can form the basis of a categorical representation [159], making them useful when investigating what effects subtle changes to a stimulus (e.g. an emotional face, or a body posture) has upon how people emotionally interpret these [42]. Furthermore, given that dimensions provide a numeric representation, they allow researchers analyse them using statistics and machine learning methods.

Dimensional approach however is not without problems and shortcomings. Firstly, and perhaps more importantly, is that as with the basic emotion theories, there are disagreements with respect to both the number of dimensions an emotional space should consist of, but also what the different dimensions represent. This is a practical problem in that in situations where there are only two dimensions of e.g. valence and arousal, certain states such as Fear and Anger are difficult to differentiate [59, 187]. As such, this has resulted in a large number of different emotional spaces, with ongoing debate as to which spaces are most optimal. This issue was discussed in more details in the Chapter 2, section 2.2.2, and it still remains very much open [42]. For the purpose of these thesis we use the emotional dimensions of Valence and Arousal as they allow differentiation between the basic emotions of Happiness, Sadness and Surprise. Additionally, we use a third dimension of Dominance to be able to differentiate between the emotions of Fear and Anger.

3.4.2 Capturing Emotion from People

Capturing emotion from human subjects is possible in two ways: using implicit and explicit methods [28, 82]. Implicit methods measure behavioural characteristics of a person (heart rate, skin resistance, respiration rate, and others, see Zeng et al. [187] for overviews), while explicit methods require that subjects self report and input data directly, suggesting or choosing emotional labels or adjectives, selecting an emotional face, etc. The work presented in this thesis has only employed the latter, as the use of implicit measures limits the amount of comparison that may be made with the related prior studies on emotional expressions and behaviours in social agents. The previous section outlined the two main approaches that have been established with respect to how emotions can be represented in artificial systems that have an emotional component: categorical labels and emotional dimensions, and discussed their respective benefits and limitations.

There are a number of different tools that have been developed for emotional measurement based around emotional dimensions, namely the Self Assessment Manikin (SAM) [20], EMuJoy [113] and the AffectButton [27].

EMuJoy is a tool that has been developed for capturing peoples' emotional ratings of musical pieces. With EMuJoy, two dimensions are shown on screen, Arousal and Valence, with a cursor that shows the current position in the two-dimensional affect space. The cursor takes the form of a small expressive face that dynamically changes as the cursor is moved around the input space, to represent the general affect of the current location. This tool also facilitates a history of affective measurements in the form of a worm tail which shows the previous inputs by the user in their chronological order.

The AffectButton is a tool that shows only an expressive face that changes dynamically as the mouse cursor is moved around the input space. Each face is also encoded into a three-dimensional coordinate where the dimensions correspond to Pleasure, Arousal and Dominance. What is unique about this tool compared to the others outlined above is that the underlying affective dimensions are completely hidden from the subject, and thus there is no need to even mention the notion of affective dimensions to users.

3.4.3 Self Assessment Manikin

The SAM is a picture-orientated tool that is designed to assess the Pleasure, Arousal and Dominance dimensions independently. Graphical images are shown to depict major points along each dimension. For the pleasure dimension, the images shown an agent (similar to a humanoid robot) with differing facial gestures ranging from a large happy

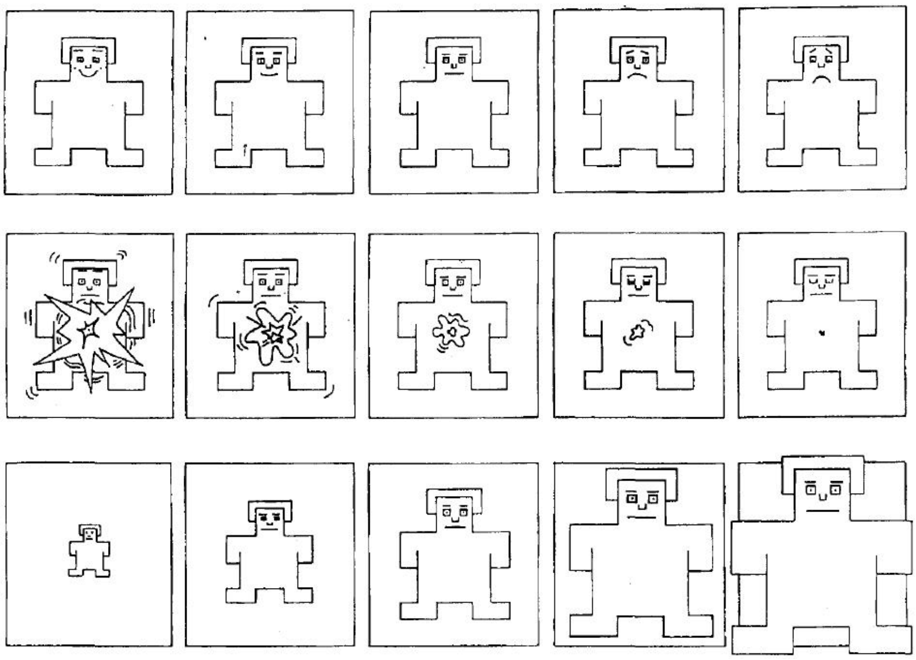


Figure 3-6: *Self Assessment Manikin. The top row presents the dimension of Pleasure/Valence. The middle row presents the dimension of Arousal. The bottom row presents the dimension of Dominance.*

smile to an unhappy frown. Arousal is depicted with a figure with a wide-eyed excited face to a sleepily and relaxed face. Dominance is shown with the figure with varying physical size, which relate to the amount of control that the figure has with respect to the surrounding environment (the surrounding box in this case): a large figure translates to high control and thus dominance, while a small figure translates to the figure having little control.

One of the benefits of this tool is its independence from the language the human subjects speak. This makes SAM convenient to use with the international students, who are the majority of this work's subjects. What is unique about the SAM tool compared to the others outlined above is that the visual representation of emotion is produced with the figure of an agent, not the face. This creates a link with the bodily expression of a robot presented to the subjects in our studies, and this is why this tool was selected as the emotional measuring tool of choice during the experiments presented in this thesis.

3.5 Summary

This chapter has provided details regarding methodological tools that have been employed in during the work informing this thesis. Firstly, the review of four approaches to present emotional expressions of robotic agents was presented, that included interaction with a physical robot, video recordings of a robot, Wizard of Oz and simulated computer-based robotic agent. Based on the discussed advantages of each method, two approaches were selected to be used in the studies addressing this thesis: real world observations of a robot for the study presented in Chapter 4 and video recordings of a robot behaviours in the studies presented in Chapters 6, 7 and 8. Next, a description of two non-humanoid robots used as the platform for the experimental studies was presented. Finally, following a brief description and discussion regarding the two main schools of thought regarding representations of emotional categories and emotional dimensions, issues surrounding the measurement of emotion and tools developed to do this were presented. This chapter ended with a detailed description of the affective measuring tool of choice, the Self Assessment Manikin, and how it has been used in this work.

CHAPTER 4

TOWARDS EMOTIONAL EXPRESSIVITY IN ROBOTS: PRELIMINARY EXPLORATORY STUDIES

4.1 Introduction

In order to benefit human-robot interaction, robot emotional signals should first of all be clearly expressed in a way comprehensible for humans. For robot emotional signals to function effectively in human interactions, it is necessary to consider the robot's internal state with respect to its ongoing activities, so that human collaborators can create relevant mappings from the set of signals it produces. In other words, *artificial emotions* are a necessary prerequisite for generating intelligible robot emotional signals. Without this step, robot emotional signals are unlikely to serve interactions well.

In this chapter we consider the potential of artificial robot emotions to serve as coordination devices in human-robot teams. We report an investigation of the potential for simple features of robotic embodiment to facilitate dynamic emotional signalling in a manner that allows interpretation by human observers. In such a way this chapter addresses the first research question RQ1 of the thesis formulated as follows: "RQ1: Do people perceive robotic bodily expressions as having different emotional meanings, and if so, are people consistent in the meaning they perceive?" The broad aim of this work is to try to find a general scheme for communicating task-relevant internal states of a robot in a way which is both meaningful and intuitive for humans, with the ultimate aim of supporting successful social coordination between human and robot collaborators.

The chapter is organized as follows. We begin by setting out our methodological approach, defining the main research questions of this study and the measures we selected for addressing the problem. We then present two exploratory studies, the first based on still images of robot poses and the second based on *live* episodes of embodied robot emotional signalling. Details of each study are given together with its results. The results of the two studies reveal the tendency of people to assign an emotional meaning to the observed robot expressions, given a simple context. Both a qualitative and quantitative analysis of the data collected through the studies shows that the majority of participants interpret robot expressions in an emotional way. The differences between emotional and non-emotional interpretations of robot's behaviours are statistically significant for all the presented expressions that were designed to be emotionally charged. Besides, the qualitative thematic analysis reveals that in addition to assigning an emotional interpretation to the robot's expressions, people tend to relate robot emotional state to a predicted future or previous interaction. The results also imply that people can consistently recognize the emotional meaning they perceive in observed a robot's bodily expressions. The values of recognition ratio detected through two reported studies exceed the chance level for each recognized emotion of the robot.

We conclude the chapter with a discussion of the results and suggest both implications for HRI and directions for further work.

4.2 Method

A series of studies was conducted in order to better understand whether a non-humanoid robot can express artificial emotions in a manner that is understandable for human. The studies have been conducted to examine three questions:

1. What meaning do people assign to the observed non-humanoid robot expressions?
2. Can people consistently recognize as emotional non-humanoid robot expressions presented to observers in a static or dynamic manner?
3. Can people consistently recognize robot intentions based on observed robot expressions?

In the first study participants were presented with static pictures of different robot expressions and asked to guess the observed robot emotion. In the second study, participants viewed dynamic expressions of the robot in a real time and were asked 1) to describe what the robot was doing in their own words (deliberately without asking participants to use emotional terms); 2) to guess the meaning of the observed expression by choosing from a controlled list of emotional terms, and 3) to guess the possible future robot actions, based on their beliefs about the meaning of the expression they had just seen. We have been experimenting with the robot E4, which was described in more details in Chapter 3, section 3.3.1.

We prepared a controlled list of emotional terms which was presented to the participants as a list of possible options to choose from when characterizing the robot

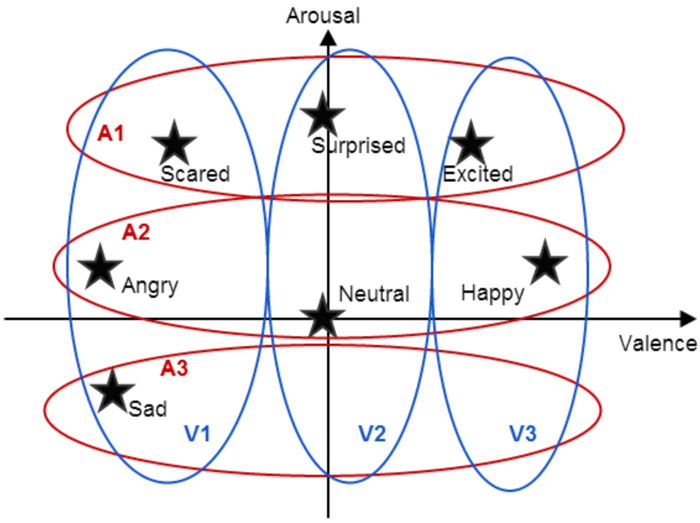


Figure 4-1: *Proposed emotional terms in a valence-arousal circumplex model.* A1, A2 *and* A3 *sections correspond to high, average-to-none and low arousal respectively.* V1, V2 *and* V3 *sections correspond to negative, neutral and positive valence respectively.*

expressions. The list was created with an intention to balance proposed options in term of both valence and arousal. The main list consisted of seven emotional terms - *scared, surprised, excited, angry, neutral, happy* and *sad*. Later we have included additional terms *other* and *don't know* to the main list in order to provide the participants with additional options to express their opinions. The emotions from the main list were balanced in the valence-arousal circumplex model [150] over the dimensions of both valence and arousal, as shown in Figure 4-1. Three options i.e. *scared, angry* and *sad*, belonged to a negative valence section V1; two options i.e. *surprised* and *neutral*, belonged to a no-valence section V2; and two more options i.e. *happy* and *excited*, belonged to a positive valence section V3. On the arousal dimensional area the *sad* option belonged to a low arousal section A3; *scared, surprised* and *excited* belonged to a high arousal section A1; and *angry, neutral* and *happy* were in the middle section that corresponds to an average-to-none arousal level in the section A2.

4.3 Measures

Two statistical measures were used to estimate the extent to which the robot emotional signals were interpreted consistently by our participants. These measures were used in both study 1 and study 2. However, we adopted a mixed-methods approach to our exploration of human responses to robot emotional signalling in study two by conducting a thematic analysis of the qualitative data provided by our participants. The additional qualitative data was of great importance in providing meaning to the statistical results we found, given that we are committed to relating inferences about emotional signals to socially coordinated patterns of action from the perspective of human collaborators.

The first statistical measure represented the frequency of the term most often selected by participants, without regard to any initially intended emotion, and was based on the recognition ratio for each expression. The recognition ratio $r(p_i, e_j)$ for each picture or real-time expression was calculated as defined by Eq. 4.1.

$$r(p_i, e_j) = \frac{N_{ij}}{N} \tag{4.1}$$

where p_i = picture or expression number i , e_j = selected emotional code number j; N_{ij} = number of responses (p_i, e_j); N = total number of responses.

The second measure was used to estimate consensus of judgement among participants: the Fleiss' Kappa (κ) value [57]. The Fleiss' kappa value was used for measuring the agreement between the users regarding the observed robot emotion, as well as an expected robot's intention. The kappa value is a statistical measure for assessing the reliability of agreement between a fixed number of raters and is defined by Eq. 4.2, 4.3 and 4.4.

$$\kappa = \frac{\bar{P} - \bar{P}_e}{1 - \bar{P}_e} \tag{4.2}$$

$$\bar{P} = \frac{1}{Nn(n-1)}(\sum_{i=1}^{N}\sum_{j=1}^{k} n_{ij}^2 - Nn) \tag{4.3}$$

$$\bar{P}_e = \sum_{j=1}^{k} p_j^2 \tag{4.4}$$

The factor 1 - $\bar{P}_e$ gives the degree of agreement that is attainable above chance, and, $\bar{P} - \bar{P}_e$ gives the degree of agreement actually achieved above chance. If the raters are in complete agreement then $\kappa = 1$. If there is no agreement among the raters (other than what would be expected by chance) then $\kappa \leq 0$.

In our studies: $i = 1, . . . , N$ represents the participants, n is the number of pictures of Lego robot in the first study and the number of dynamic real-time robot expressions in the second study (with n_{ij} the number of ratings per picture/expression) and $j = 1, . . . , k$ represents the possible answers (given in questionnaires). An interpretation of the κ values has been suggested by [95], and is presented in Table 4.1. This table is however not universally accepted, and can only be used as an indication [72].

Kappa Statistics	Strength of Agreement
< 0	Poor
0.01–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–1.00	Almost perfect

Table 4.1: *Benchmark for strength of agreement indicated by κ value. Adapted from [95]*

4.4 Study 1

4.4.1 Study 1 Apparatus

We programmed six combinations of robot movements based on a basic arousal-valence underlying model [150], with approach and avoidance of the robot's neck and its whole body as a metaphor for valence and reflecting the arousal concept by raising its eyebrows. Then we photographed each combination from two angles – front and $^3/_4$ views. These two views were selected for presenting the robot's expressions as these views are considered to be canonical for a large number of objects [178]. Moreover, the combination of the two views has been proven to produce better face recognition performance [91]. The six pairs of pictures were used to construct a questionnaire provided to participants.

4.4.2 Study 1 Participants

27 people (14 females and 13 males) agreed to participate in a study to determine whether our simple set of valence-arousal robotic gestures could be interpreted as emotional signals. 18 had no previous experience with any kind of robots, 4 considered themselves as roboticists, and the rest had some previous interaction experience with robots. 18 were over 40 years old, 3 were between 30 and 39 years old, and six were between 20 and 29 years old.

4.4.3 Study 1 Procedure

For each pair of images, participants were asked to select the most appropriate emotional term from a set of possible responses: sadness, happiness, anger, surprise, excitement, fear, other, no specific emotion and don't know. They were also asked to use a five-point Likert scale to rate their degree of confidence making that judgement.

	Expression 1	Expression 2	Expression 3	Expression 4	Expression 5	Expression 6
Surprised	**29.6%**	3.7%	**51.9%**	**33.3%**	3.8%	16.0%
Scared	3.7%	11.1%	22.2%	22.2%	**42.3%**	4.0%
Excited	14.8%	11.1%	18.5%	18.5%	0.0%	**36.0%**
Sad	11.1%	**40.7%**	0.0%	0.0%	30.8%	0.0%
Neutral	22.2%	14.8%	0.0%	3.7%	11.5%	0.0%
Happy	11.1%	0.0%	7.4%	14.8%	0.0%	12.0%
Angry	3.7%	14.8%	0.0%	3.7%	3.8%	12.0%
Other positive	3.7%	0.0%	0.0%	3.7%	0.0%	8.0%
Other negative	0.0%	3.7%	0.0%	0.0%	7.7%	0.0%
Don't know	0.0%	0.0%	0.0%	0.0%	0.0%	12.0%

Table 4.2: *Recognition ratio for the expressions observed in Study 1. The highest recognition ratio for each expression is presented in bold.*

Emotional Description	Fleiss' κ value	Interpretation of κ value
Scared	0.08	Slight agreement
Not emotional at all	0.05	Slight agreement
Surprised	0.14	Slight agreement
Angry	0.01	Slight agreement
Excited	0.05	Slight agreement
Sad	0.19	Slight agreement
Happy	0.01	Slight agreement

Table 4.3: *Participants' agreement regarding the robot's emotions in Study 1*

4.5 Results of Study 1

The most frequently selected codes for these expressions were *surprised, sad, scared* and *excited.* The values of recognition ratio for each presented expression are given in the Table 4.2. The recognition ratio for such emotions as *surprise, fear, excitement* and *sadness* were the highest (52%, 42%, 36% and 41% respectively). The lowest recognition ratio was for the emotion of *anger*, as shown in the Table 4.2.

The values of participants' confidence of the observed robot's emotion, on average, were quite similar for each emotional expression and differed in the range between 3.29 (SD = 0.80) and 3.79 (SD = 1.15), where '1' was *the least confident* and '5' was equal to *the most confident*, as presented in Table 4.5. The confidence levels for the options *don't know* were ignored because this option does not represent any specific emotion.

The recognition ratio for each expression observed by the participants was higher than the recognition ratio expected by chance (the chance level was calculated as 10%). However, the Fleiss' κ value calculated for each expression only showed a slight agreement between participants for each of recognized emotions, as shown in Table 4.3.

Reflection on study 1 identified three major methodological limitations: 1) an image of the end point of an expressive state may not convey the same meaning as the experience of seeing it performed in real time; 2) although it is assumed that people will naturally use anthropomorphic terms to describe non-human agents, forcing participants to use emotional labels undermines the validity of claims that emotional terms are spontaneously appropriate for robot signals, and 3) there was no context given to participants within which to interpret the signals.

4.6 Study 2

4.6.1 Study 2 Apparatus

The second study was designed to address the limitations discussed above. In the second study we programmed five dynamic expressions, each intended as an emotional signal behaviour based on the combinations of the two movements of the same Lego robot and presented them to the participants in real-time, providing them with an emotionally neutral statement of the context in which the robot was acting. We also give our participants the opportunity to describe the robot‘s behaviour in their own words before asking them specific questions about emotional expression (see Appendix A). A paper form was provided to the participants for them to describe the robot behaviour in their own words. A Matlab programmed questionnaire was presented to participants for selecting Likert scale responses to a set of questions (see Procedure below).

4.6.2 Study 2 Participants

The second study was conducted during a Bath University Open Day. 28 people (6 females and 22 males) agreed to participate in a study, ranging in age from 17 to 53 (M = 17.8, SD = 0.99), interested in human-robot interaction.

4.6.3 Study 2 Procedure

In the second study, conditions 1 and 2 were examined by presenting the five dynamic signal behaviours to participants successively in real-time. Each condition took approximately five minutes to complete. By way of context, participants were asked to consider that the robot was exploring an unfamiliar space when it noticed something. The language used to state context was deliberately intended to avoid leading participants to use emotional terminology rather than any other form of description.

Condition 1 required the participants first to explain in their own words what the dynamic expressions meant to them by writing whatever they liked on a paper form. Condition 2 repeated the same presentation of dynamic expressions but this time asked them to select a term of best fit from a fixed list of emotional terms. The participants were also asked to use a five-point Likert scale to rate their degree of confidence (1 - least confident, 5 - most confident) making that judgement. Finally, the participants were asked to choose the most likely “what happens next” option from another prepared

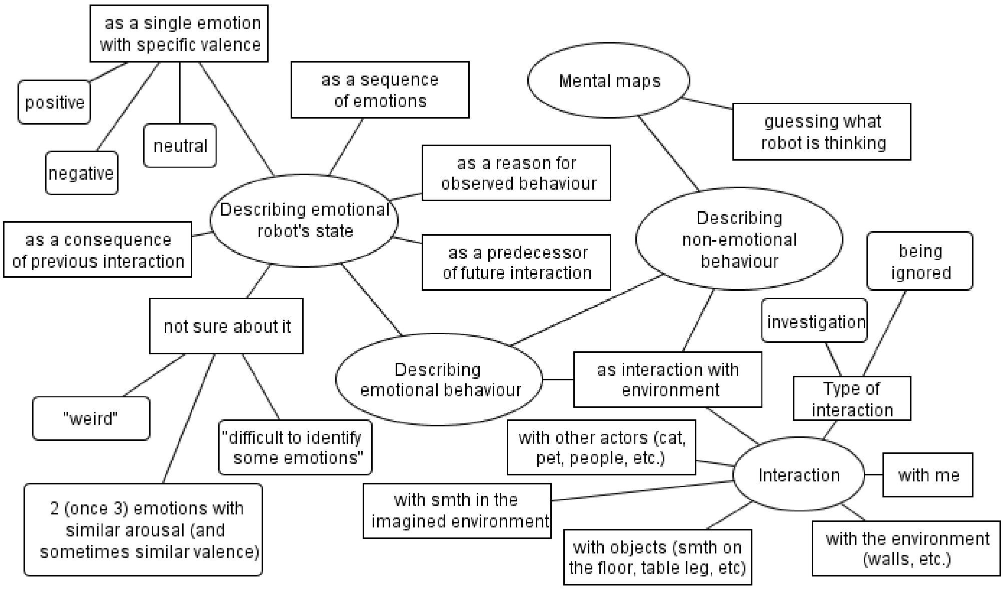


Figure 4-2: *Initial thematic map, showing five main themes that became apparent from the thematic analysis. Main themes are presented as ovals.*

list. All the questionnaires provided to the participants were in an electronic form in a Matlab environment.

4.6.4 The Thematic Analysis

The thematic analysis [152] was conducted for analysing qualitative data collected under the Condition 1 of the second study. Thematic analysis was advantageous for this purpose as it could offer an accessible and theoretically flexible approach to analysing qualitative data, produce a useful summary of key features, patterns and themes of a body of data, highlight similarities and differences across the data set and allow for social interpretations of data [21]. As a result of thematic analysis we produced an initial thematic map of five main themes shown in Figure 4-2. The main themes developed at this stage of the analysis were: 1) emotional robot's state, 2) emotional robot's behaviour, 3) non-emotional robot's behaviour, 4) mental maps, and 5) interaction.

From this early stage thematic map we realized the relationship between themes (presented as circles in the Figure 4-2) and different levels of sub-themes. A number of participants described the robot's expressions as an internal robot's emotional state emerged as a consequence of previous robot's interaction with its environment. The same explanation was very often seen in the descriptions of robot's behaviour, both when explained in an emotional and non-emotional tone. It is likely that people associated the changes of internal state with a previous interactional experience of the robot and made assumptions regarding that interaction. In the same way, many par-

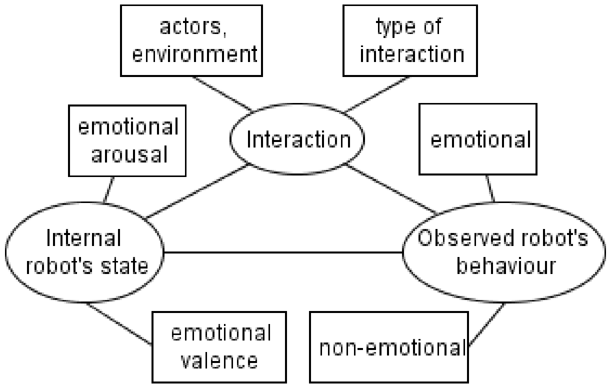


Figure 4-3: *Final thematic map, showing three final main themes, presented as ovals.*

ticipants made associations between the emotional state of the robot and its behaviour they observe. For some of the participants, the behaviour was a predecessor of a future interactive act, for others it was a consequence or an accompanier. We explain such assumptions as a process when participants were creating mental maps about the presented robot and its surroundings in both place and time.

The interaction itself was described by participants in several different ways. The majority of participants described the object of the imagined interaction, which was a person himself, other unspecified people, non-human actors like pets and cats, different objects like table legs, parts of the environment like walls and floor. However, several participants were more specific about the type of the interaction rather than the object the robot interacted with. In the description of robot's expressions they mentioned the words "investigating" and "investigate", thus defining the type of interaction they imagine. One person mentioned that the robot "was ignored" previously thus suggesting the previous unsuccessful interaction between the robot and some actor. The importance the concept of interaction had in the descriptions of participants means that people tend to directly relate emotional states and emotional behaviour with interactive acts, either previous, current or future. If such an interaction wasn't observed people just created it in their mind and related to the future or the past.

At the final stage we developed the final thematic map showing three main themes - internal robot's state, observed robot's behaviour and interaction, as shown in Figure 4-3. These three main themes were developed by combining the different sub-themes of similar types into more general groups. The more general themes of the final map were produced by refining all the themes in the initial map, identifying the 'essence' of what each theme was about and reducing the complexity. For example, several sub-themes of the main *Interaction* theme in the initial thematic map, such as "Interaction with me", "Interaction with the environment", "Interaction with other actors", "Interaction with smth in the imagined environment" and "Interaction with objects", were all com-

	Expression 1	Expression 2	Expression 3	Expression 4	Expression 5
Surprised	**57.1%**	21.4%	0.0%	3.6%	14.3%
Scared	7.1%	**67.9%**	0.0%	0.0%	3.6%
Excited	7.1%	7.1%	0.0%	0.0%	**32.1%**
Sad	10.7%	0.0%	14.3%	14.3%	3.6%
Neutral	0.0%	0.0%	**57.1%**	0.0%	0.0%
Pleased	3.6%	0.0%	0.0%	3.6%	0.0%
Angry	3.6%	0.0%	0.0%	3.6%	**35.7%**
Curious	3.6%	0.0%	28.6%	**67.9%**	3.6%
Other emotion	7.1%	3.6%	0.0%	7.1%	7.1%

Table 4.4: *Recognition ratio for the robot's expressions observed in Study 2. The highest recognition ratio for each expression is presented in bold.*

bined into one more general sub-theme in the final map called "Interaction with actors, environment". We decided to exclude the *Mental maps* theme from the diagram, because as we have explained earlier the creation of mental maps is a consistent process consisting of investigating robot's internal state, the meaning of its behaviour and its interaction with the environment. Thus, creating mental maps is an overwhelming continuous process covering both understanding robot's internal state and behaviour and actually interacting with a robot. The remaining three themes nicely represent the famous "sense-act" reactive robotic paradigm [29], where changes in the internal robot's state represent the *sense* part of the loop, and the theme represents the *act*, i.e. reactive response. The interaction theme here represents the loop itself.

4.7 Results of Study 2

For the dynamic robot expressions presented to the participants in the second study the recognition ratios were allocated as in the Table 4.4, with the highest recognition ratio for the expressions 2 and 4 recognized as *scared* and *curious* respectively.

The values of participants' confidence of the observed robot's emotion, on average, were spread more widely compared to Study 1 and differed in the range between 1.50 (SD = .50) for *happiness* and 3.93 (SD = 0.81) for *surprise*, where '1' was *the least confident* and '5' was equal to *the most confident*, as presented in Table 4.5.

The Fleiss' κ value calculated for each expression showed moderate agreement for the emotion considered to be *scared* and for a non-emotional robot's expression. *Curious, surprised* and *angry* robot's emotions were interpreted with a fair agreement. Emotions interpreted as *excited* and *sad* had only a slight agreement, and for *pleased* participants did not manage to agree, having a Fleiss' κ value smaller than 0, as shown in Table 4.6.

There was a slight agreement between participants on the expectations of what the robot was going to do next – moving forwards/backwards, staying still, turning or

	Study 1		Study 2	
	Mean	St.Dev.	Mean	St.Dev.
angry	3.40	1.07	2.92	0.86
excited	3.48	0.70	3.54	0.63
happy/pleased	3.55	0.50	1.50	0.50
neutral	3.79	1.15	3.69	1.04
sad	3.57	0.66	3.08	0.95
scared	3.42	0.57	3.86	1.18
surprised	3.47	0.60	3.93	0.81
curious	-	-	3.69	1.18
other	3.29	0.80	3.69	1.04

Table 4.5: *Mean values and standard deviation values for the confidence of the observed robot's emotion in Study 1 and Study 2.*

Emotional Description	Fleiss' κ value	Interpretation of κ value
Scared	0.50	Moderate agreement
Not emotional at all	0.50	Moderate agreement
Curious	0.38	Fair agreement
Surprised	0.24	Fair agreement
Angry	0.24	Fair agreement
Excited	0.14	Slight agreement
Sad	0.01	Slight agreement
Pleased	-0.01	Poor agreement

Table 4.6: *Participants' agreement regarding the robot's emotions in Study 2.*

Robot's intention	Fleiss' κ value	Interpretation of κ value
Move forward	0.132	Slight agreement
Turn	0.028	Slight agreement
Stay still	0.033	Slight agreement
Move backwards	0.108	Slight agreement
Something else	0.028	Slight agreement
Don't know	0.070	Slight agreement

Table 4.7: *Participants' agreement regarding the robot's intentions in Study 2.*

doing something else. The highest values of agreement were presented for the choices *move forward* (κ = 0.1322) and *move backwards* (κ = 0.1078). However, none of the options exceeded the boundaries of only a slight agreement, as shown in Table 4.7.

4.8 Discussion

Let us examine how the two studies presented in this chapter answered our different research questions.

4.8.1 What meaning do people assign to the observed non-humanoid robot expressions?

According to the results of the second study we can state that the majority of people assign emotional meaning to the observed robot expressions, given a simple context. Table 4.8 shows that the majority of participants interpret robot expressions in an emotional way. Chi-squared test shows that the differences between emotional and non-emotional interpretations are significant for all the expressions except one: there is the only expression where the non-emotional interpretation exceeds the emotional one, although the difference is not significant ($\chi^2(1, N = 28) = 1.27$, $p = .26$), and it is the *neutral* expression where the robot is not moving its hands, neck and eyebrows at all. For all the other expressions an emotional interpretation is selected significantly more often than non-emotional.

The tendency to assign emotions to robot expressions repeats in the other condition of the second study. The results of the qualitative data analysis show that 46% (13 out of 28) of participants describe the observed expressions as emotional behaviour, and another 46% (13 out of 28) – as an emotion itself. Less than 1% (2 out of 28) describe observed robotic expressions as a non-emotional behaviour.

The thematic analysis shows that in addition to assigning an emotional interpretation to robot expressions, people tend to relate robot emotional state to the predicted future or previous interaction. 63% of those explain the observed robot emotional state as a consequence of a previous interaction, the rest of the answers distributes between

Expression	Emotional	Non-emotional	Chi-squared statistics
1	22	5	$\chi^2(1, N = 27) = 10.70$, $p = .001$
2	21	6	$\chi^2(1, N = 27) = 8.33$, $p < .005$
3	11	17	$\chi^2(1, N = 28) = 1.27$, *ns*
4	19	9	$\chi^2(1, N = 28) = 3.57$, $p = .05$
5	20	8	$\chi^2(1, N = 28) = 5.14$, $p < .05$

Table 4.8: *Emotional and non-emotional interpretation of robot's expressions in Study 2.*

explaining the meaning of the observed emotion as 1) a reason for observed behaviour, 2) a tool for interacting with people and 3) a predecessor of a future interaction.

4.8.2 Can people consistently recognise as emotional non - humanoid robot expressions presented to observers in a static or dynamic manner?

The values of recognition ratio exceed the chance level for each recognized emotion but the recognition ratios in our studies are not very high, compared to similar previous experiments completed by [154] [36] and [169], as presented in the Table 4.9. However, comparing the ability to represent emotional states of our robot that has only three DoF with other robots presented in the table, we consider the given results as very satisfactory. The possible explanations for lower recognition levels could be 1) in our first study the participants viewed only the static pictures of the expressions and this decreased the recognition rate, 2) in our studies we used the movements of the whole robot body together with the only one 'facial' feature - eyebrow, while in the previous mentioned studies the emotions were represented by facial expressions only.

The results show a significant difference between an average recognition ratio for positive (section *V3* in Figure 4-1) and neutral (section *V2* in Figure 4-1) emotions, $t(6) = 2.25$, $p < 0.05$ (one-tail), as well as between an average recognition ratio for positive (section *V3* in Figure 4-1) and non-positive (sections *V1+V2* in Figure 4-1) emotions, $t(12) = 1.78$, $p < 0.05$ (one-tail), with a lower recognition ratio for positive emotions in both cases.

The results also show a significant difference between an average recognition ratio for high arousal (section *A1* in Figure 4-1) and average arousal (section *A2* in Figure 4-1) emotions, $t(10) = 2.43$, $p < .05$, as well as between an average recognition ratio for high arousal (section *A1* in Figure 4-1) and other arousal (sections *A2+A3* in Figure 4-

	Our study 1	Our study 2	Feelix	Probo	Eddie
surprise	52	57	37	70	75
fear	42	68	16	65	42
sad	41	14	70	87	58
happy/excited	36	32	60	100	58
disgust	-	-	-	87	58
anger	15	36	40	96	54

Table 4.9: *Comparison of the emotion recognition results in the rpesented Studies 1 and 2, and the prior studies with the robots Feelix, Probo and Eddie, partly adapted from [154]*

1) emotions, $t(12) = 2.59$, $p < 0.05$, with a higher recognition ratio for high arousal emotions in both cases.

The participants observing dynamic emotions have in general a significantly higher level of confidence (M = 3.52, SD = 1.03) over those observing static emotions (M = 3.49, SD = 0.74), $t(251)$ = -0.265, $p < 0.001$. However, having in mind specific emotional expressions only for the emotion of *scare* there is a significant difference in a confidence level between the participants observing static images (M = 3.40, SD = 0.57) and those observing dynamic real-time expressions (M = 3.86, SD = 1.21), $t(45)$ = -1.71, $p < 0.05$.

4.8.3 Can people consistently recognise robot intentions based on observed robot expressions?

The results of our qualitative analysis show that the participants relate their observations of the robot's emotional signals to its interaction with the environment, and some sense of its previous experience. They thus set their interpretation into an event timeframe, whether as a matter of feelings attributed to the robot at that moment, as a result of a recent activity, or in anticipation of the robot's next action. Based on these statements, it is clear that our participants were making systematic attempts to interpret the robot's state given its behaviour. We expected the observers to have at least a moderate agreement about robot's immediate intention to act, based on the emotion attributed to it. However, the results of the inter-rater agreement analysis show that the low overall agreement between participants regarding the robot's expected action, with a highest Fleiss' κ value of 0.132 for the agreement regarding robot's intention to moving forward. Thus, the results of the studies we have reported here cannot support the statement that people can consistently recognise robot intentions based solely on the set of robot expressions we designed. The question of robot's intention recognition from its behaviour raises interesting issues and should be explored in future research. Although it is not possible to draw definitive conclusions from this study, it underlines the importance of setting any expressive behaviour into a context of action. In our work, the context of action will be set by joint work and so inferences about artificial emotion must also include ethical considerations.

4.8.4 Responsible Design of Artificial Emotions for Social Coordination

We introduced our work with a focus on non-humanoid robots as potential members of human-robot teams. The decision to operate outside of the constraints imposed by humanoid forms have a number of advantages. It is possible to explore a very wide range of forms and scales, primarily driven by a concern to create robots whose form fits their functional purpose. At the same time, we have arguably created a more difficult interpretative problem for the human team member, who will perhaps be more ready to consistently attribute emotional expressions to humanoids than to the expressive behaviours enacted by robots that are transparently mechanical. In other words, the work of working together creates a requirement for collaborators to infer one another's concerns and attitudes and so there could be a strong social function afforded by adopting humanoid forms. Humanoid forms may promote anthropomorphic attributions of thoughts and desires.

Our treatment of affect has been deliberately framed in terms of task-related responses to events in the context of collaboration: we have not attempted to promote a model that could support the attribution of more durative moods (e.g. 'the robot is annoyed') or sentiments (e.g. 'the robot thinks I am unkind'). In our introduction, we refer to 'empathic competence', in part to suggest the ethical uncertainty of work in this research area. Researchers who are working towards the construction of emotional robots must consider the potential risk of creating a mechanism that fools human collaborators into believing robots are capable of moral agency and moral reflection. Although we are working towards the possibility of robots becoming team members, we are not attempting to create a framework for people to put themselves at risk in order to believe that robots are capable of intervening to protect them when such action is simply not possible within their programming. We believe that maintaining a strong task focus for the interpretation of emotion signals will help to confront this ethical problem. It has been argued that the machine-nature of a robot should be made apparent to people who encounter it, in part to guard against inappropriate or dangerous attributions [33]. Creating an emotional signalling system for non-humanoid robots should retain their value as social coordination mechanisms whilst at the same time preserving their transparently mechanical nature.

4.9 Conclusion

This chapter has presented research concerning expression of artificial emotions in human-robot interaction. As in human non-verbal communication, expressive movements of the body and the face play an important role in HRI.

The goal of this research was to explore the relatively new research topic of facial and bodily gestures communication in social robots using a simple Lego robot as a case study and thus find a way of communicating internal robot state to humans in a both meaningful and intuitive way. We posed three main research questions: What meaning do people assign to the observed non-humanoid robot expressions? Can people consistently recognise as emotional non-humanoid robot expressions presented to observers in a static or dynamic manner? Can people consistently recognise robot intentions based on observed robot expressions?

We investigated these questions using two paired studies. Studies 1 and 2 were exploratory in that they tested perception of artificial emotions in robot expressive movements of its body and one facial feature in a simple situational context.

The results from this study demonstrate that even very simple movements of a social robot with only three DoF can convey emotional meaning, showing promise for designing non-humanoid robots that could serve as socially coordinated members of human-robot teams. In particular, this suggests that when people attribute emotional states to a robot, they typically apply an event-based frame to make sense of the robotic expressions they have seen. This suggests that it is possible to create effective robot collaborators without an expressive human-like face, legs, moveable fingers or wrists. We have further argued that such an approach could help researchers and designers to contain the risk of inappropriate attributing robots with durative affective states, and moral agency, by emphasising their machine-like nature.

The results of this research provide a reason to believe that, in a context of a joint human-robot activity, it should still be possible for interaction designers to use interface elements such as body movements or extremely simple facial expressions to increase the expressive power of robots and thus increase a social coordination between human and robot in a human-robot team.

In the next chapter we will present an effort to provide a systematic approach to developing emotions in robots in terms of a computational model of emotion that links robot actions to emotional expressions. Further work in Chapter 6 will explore the effect of moving the different parts of the robot body on the interpretation of artificial emotions in HRI.

CHAPTER 5

EMOTIONALLY DRIVEN ROBOT CONTROL ARCHITECTURE FOR HUMAN-ROBOT INTERACTION

5.1 Introduction

In the previous chapter, the concept of emotion in an embodied agent was discussed as a highly transient affective reaction. As such, emotions are triggered in response to an agent's perception of its dynamic operational environment. An agent's emotional reactions thus depend on how the state of the environment is consistent with or obstructive towards its interests or goals. Some stimuli are desirable and some are undesirable with respect to task progress. That is, where conditions cause a change to an agent's computation of task progress, it could register a state that is positive or negative with respect to the attainment of a goal. We also found that the human observers can consistently recognize as emotional non-humanoid robot expressions designed in a specific way, and they can distinguish between the emotions represented on distant point of a valence-arousal circumplex area.

This chapter presents a computational robot control architecture that incorporates artificially generated robot emotions and corresponds to the previous findings. Thus it partly addresses the second research question outline in the Chapter 1 and formulated as "RQ2. Can emotionally charged robotic bodily expressions be generated in a systematic pre-structured manner to evoke a desired emotional interpretation?" This chapter focuses on presenting an emotionally-driven computational model of action selection to control robot behaviours and its implementation as a proof of concept.

Inspired by previous research in cognitive robot architectures and human-robot interaction, we introduce a general framework for modelling artificial emotions in robots and present a model for incorporating emotions and emotional expressions into dynamic plans [31] based on Behaviour Oriented Design (BOD) [30, 34, 32].

This chapter is organised as follows. First, we summarise current computational models of emotion based on modern research in the psychology, cognitive science and neuroscience. There are currently two dominating schools of thought, appraisal and dimensional theories of emotion, both having specific advantages and disadvantages. Computational appraisal models provide a good ground for relating robot's emotional reactions to the changes in the environment with respect to the attainment of a robot's goal. However, appraisal models are limited as they do not pay appropriate attention to the structural characteristics of emotion. Dimensional theories foreground the structural and temporal dynamics of emotion but they lack the advantages of appraisal models. In our work, we consider it to be important to incorporate both a dimensional and an appraisal view of emotion into a computational model of robot control. This is why the approach of Behaviour Oriented Design is selected as a base for our work. Later in the chapter, we discuss in more details our model, explaining how it is built on BOD and clarifying each phase of emotional action selection. We then implement the described model as a proof of concept on the physical non-humanoid Lego robot E4. The results show that the robot with an implemented model is able to successfully interact with the environment and is also able both to express its internal emotional state and to change its behaviour dynamically according to the implemented action interruption scheme. The chapter ends with a general discussion of system's characteristics and limitations.

5.2 Approach

Modern research in emotion is inter-disciplinary in its nature. Modern research in the psychology, cognitive science and neuroscience highlighted the functional role that emotions play in human behaviour, as it was discussed in Chapter 2, section 2.2.2. This motivated AI and robotics research to explore computer analogues of human emotion. Computational models of emotion are based in one way or another on the main psychological theories of emotion, such as appraisal or dimensional theories that were discussed in Chapter 2, section 2.2.4.

Currently, appraisal theory dominates the work on computational models of emotion. There exists a great variety of computational models derived from appraisal theories of emotion, such as EMA [68], TABASCO [171] or PEACTIDM [106]. These models, not surprisingly, emphasize appraisal as the central process to be modelled. Computational appraisal models often encode elaborate mechanisms for deriving appraisal variables, such as decision plans [68], reactive plans [171], or detailed cognitive models [106]. Emotion itself is often less elaborately modelled in such models. Computational appraisal models have some advantages for an emotionally-driven robotic agent, as they provide a good ground for relating robot's emotional reactions to the changes in the environment with respect to the attainment of a robot's goal. However, appraisal models are limited as they do not pay appropriate attention to the structural characteristics of emotion. Moreover, appraisal models usually consider arousal as emotion's intensity. In our work, we distinguish these two concepts and define arousal as a strength of a stimulus triggering a specific emotional state, while intensity is a strength of emotion itself.

Dimensional theories emphasize different components of emotion than appraisal theories and link these components quite differently. Dimensional theories foreground the structural and temporal dynamics of core affect and often do not address emotion's antecedents in detail. Most significantly, dimensional theorists question the tight causal linkage between appraisal and emotion that is central to appraisal accounts. Dimensional theorists consider emotion as a "non-intentional" state, meaning that emotion is not about some object. Computational models influenced by dimensional theories, such as e.g. ALMA [64] or Wasabi [16], emphasize processes associated with core emotion and pay less attention to other components, such as appraisal. Core emotion is typically represented as a time-varying process that is represented at a given period of time by a point in 3-dimensional space. Computational dimensional models are most often used for animated character behaviour generation, because it translates emotion into a small number of continuous dimensions that can be readily mapped to continuous features of behaviour such as the spatial extent of a gesture. The connection between emotion-eliciting events and current emotional state is usually not maintained in dimensionally-oriented computational models of emotion. Computational dimensional models have obvious advantages for an emotionally-driven robot, as they create a feasible approximation of a natural biological system state that could fit into an explanatory model for a human collaborator. However, dimensional models lack the advantages of appraisal models and thus are not suitable for the purpose of our work.

In our work, we consider it to be important to incorporate both a dimensional and an appraisal view of emotion into a computational model of robot control. We view appraisal as the mechanism that initiates changes to the emotional state expressed using three emotional dimensions of valence, arousal and dominance. There currently exist only few computational models of emotion that are able to incorporate both appraisal and dimensional view of emotion. One of them is ALMA (A Layered Model of Affect) [64], which provides temporal characteristics of affect modelled in a three-dimensional space of pleasure, arousal and dominance. In ALMA, each temporal characteristic of affect is related to specific tasks or functions which influence the agent behaviour. Another approach, that is able to incorporate dimensional and an appraisal view of emotion, is Behaviour-Oriented Design (BOD) [30, 34, 32]. BOD is an AI development methodology that combines an iterative development process based around variable state for learning and planning with the modular, responsive behaviour-based

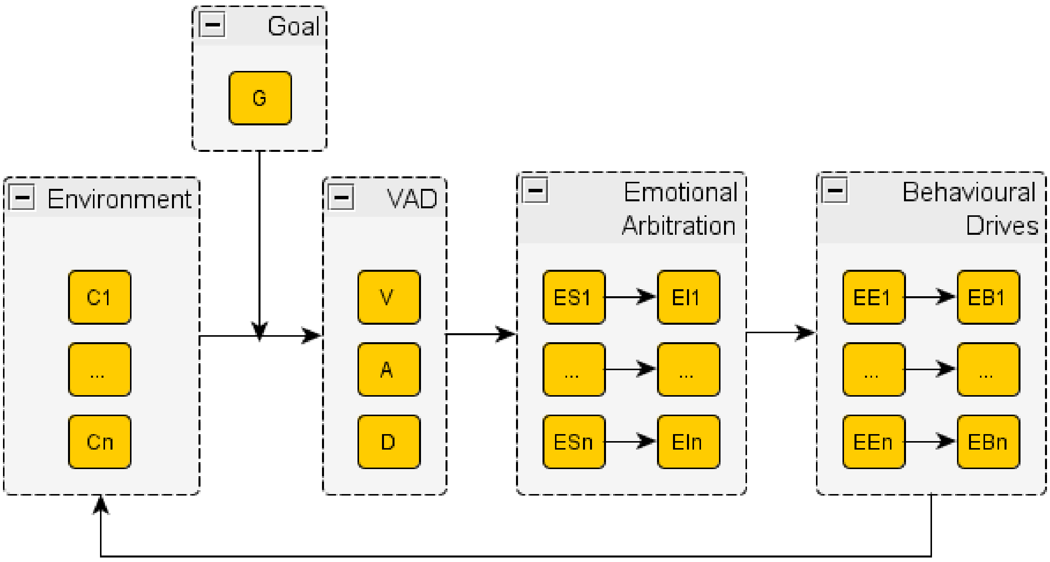


Figure 5-1: *The framework for modelling artificial emotions in robot.*

architecture. Although otherwise suitable for the purpose of our work, ALMA was originally designed for use with interactive virtual human-like conversational characters. Moreover, the emotional states of the characters in ALMA are expressed using facial expressions and conversational patterns. BOD, on the other hand, although not initially developed as an emotionally-oriented architecture, is flexible enough to incorporate a concept of emotion. Moreover, this architecture was designed to be used with cognitive mobile robots, which makes it very suitable for our purposes.

There are two parts to the BOD architecture: behavioural libraries and action selection plans. Behavioural libraries consist of actions and senses that can be called by the action selection mechanism, and any associated state or memory required to support these. Action selection plans specify the particular priorities of a given agent. The action selection mechanism consists of plans which are a hierarchy of actions with associated triggers that determine when to perform an action. Each plan is split up into a drive collection, competences and action patterns. Further details on BOD are given in its initial introduction [34] and the papers on its implementation [131].

For the purpose of our work, the robot control architecture, based on BOD, incorporates the concept of emotion by using it as a drive collection of a BOD action selection plan. Thus, the architecture integrates emotional responses and keeps track of emotion intensities changing over time. Emotions here are represented as a factor for dynamic action selection. Emotional expressions are used in conjunction as a visual cue for communicating the current emotional state to a human before the execution of an intended robot action, and are represented in the architecture as actions of a BOD action selection plan.

The more specific view of the computational model, that explains the mechanism of BOD action selection with regards to our emotionally-based architecture, is presented in Figure 5-1. The first phase of emotional action selection includes detecting specific internal and/or external conditions in the environment (C1 ... Cn in Figure 5-1). Following the appraisal view of emotion [23], the conditions are specified according to their correspondence to the following groups:

- presence of an undesired stimulus,
- presence of a desired stimulus,
- a sudden stimulus,
- presence of a threatening, overwhelming stimulus,
- delay in achieving goal.

As well as type (positive or negative), we also allow for conditions to have degree. That is, stimuli can be moderately or highly desirable, or moderately or highly undesirable. Following a dimensional view of emotion, for determining an appropriate emotional state we use a Valence-Arousal-Dominance (VAD) representation (for more detailed discussion on the emotional dimensions of valence, arousal and dominance see Chapter 2, section 2.2.2) to model basic emotional states, in a manner analogous to Russell's approach [150]. The purpose of using Russell's ideas is to create an integrated scheme for internal and external representation of robot's transient affective states that have a reasonable chance of being understood by a human observer. In the presented computational model we use emotions in a robot not for their own sake, it is a matter of creating an approximation of a natural biological system state that could fit into an explanatory model for a human collaborator. Thus, in the presented computational model arousal (A in Figure 5-1) represents the strength of a stimulus, the valence (V in Figure 5-1) shows a positive/negative value of a stimulus, and the dominance (D in Figure 5-1) shows the level of control a robot has on its current environment.

All the detected conditions influence valence, arousal and dominance values and thereby a robot's emotional state (ES1 ... ESn in Figure 5-1). For example, detecting presence of a desired stimulus generates positive valence of the emotion in the VAD module, a sudden stimulus generates positive / high arousal of the emotion, and presence of a threatening stimulus generates negative / low dominance.

Following a dimensional view of emotion, we also use intensity (EI1 ... EIn in Figure 5-1), as an additional property of an emotion. Initially, BOD architecture does not include the property of intensity. However, this concept is important for our model as it allows implementing temporal characteristics of emotion. Emotional intensity in our model is an internal state of an agent, which is changed dynamically while robot is

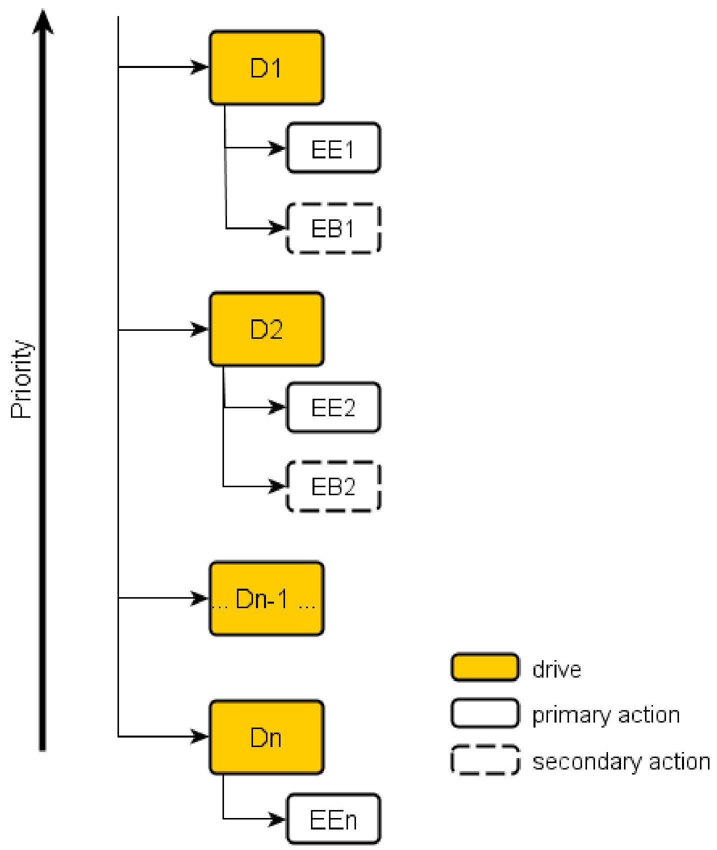


Figure 5-2: *A condensed view of a drive collection. It specifies the behaviour of the robot agent and contains four behaviour drives, prioritized top to bottom. In our model, drives correspond to emotional states.*

experiencing an emotion. Intensity depends on time, number of detected stimuli, and an impact factor of an executed behaviour.

Each emotional state relates to a specific behavioural drive of a dynamic action plan, as specified in Figure 5-2. The plan follows the characteristics of BOD action selection plan. It consists of drives (D1 ... Dn in Figure 5-2) which are prioritized based on each drive's position in the action plan. The higher the drive in the plan the higher is its priority. Each drive is designed to represent a specific emotional state earlier triggered in the robot, for example drive D1 represents the state of fear. There is a special case which is the lowest-priority drive Dn. The lowest drive should always be able to execute as it is also treated as a fallback. The primary action of each drive is always an emotional expression of the specific emotional state. It is followed by a secondary set of actions that correspond to a behaviour associated with the selected emotional drive. We use an impact factor as a property of a behaviour that depresses the intensity of the emotion this behaviour was triggered by. While the selected behaviour is being

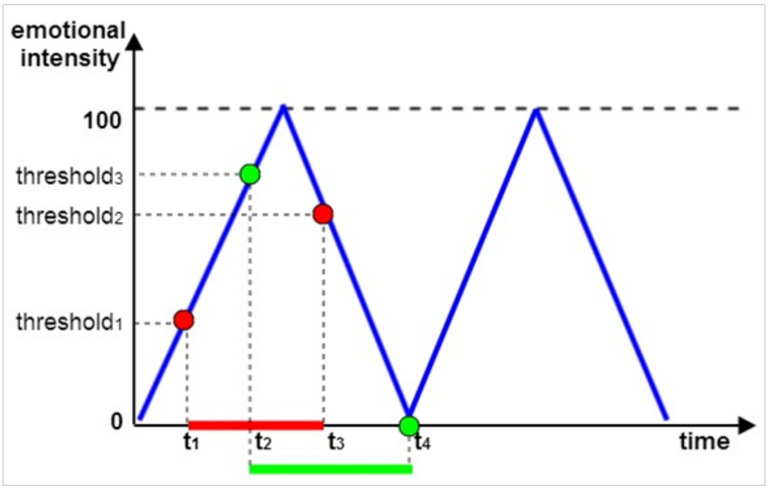


Figure 5-3: *Latched process of 'feeling' an emotion.*

executed it inhibits the intensity of the emotion it was triggered by, i.e. intensity of an emotion is a function of a behavioural impact over time.

'Feeling' an emotion or *emotional arbitration* is modelled as a latched process [35]. The original BOD architecture does not contain this option. We implemented it as an addition to our model in order to improve the process of emotional arbitration and dithering between different emotional states in real-life human-robot interaction situations. While 'feeling' an emotion an intensity of the emotion is increasing over time from zero value until the maximum threshold of 100 (percent), and is reducing back to zero after the executing behaviour inhibits it. The expression of an emotional signal behaviour starts after an increasing intensity of the emotion reaches the specified level *threshold1* and stops when the specified level *threshold2* is reached while the intensity is decreasing, as shown in Figure 5-3. The red line over the time axis shows the time period while the emotion is being expressed. The execution of the selected signal behaviour starts when the intensity of an emotion reaches *threshold3*. The execution of behaviour, if not interrupted, stops when intensity of the emotion is zero. The green line below the time axis in Figure 5-3 indicates the period of time while the selected behaviour is being executed. The execution of the selected behaviour starts when the intensity of an emotion reaches a specific level which is above the level of the start of expressing the emotion and below the maximal intensity level. The execution of signal behaviour, if not interrupted, stops when intensity of the emotion is zero.

The only way to interrupt the behaviour associated with the selected emotional drive is by having a higher activation due to an environmental interrupt which disturbs the current behaviour and either resets or memorizes the current activation. This phenomena was modelled inspired by nature. For example, an animal is calmly feeding and a predator jumps out of cover. If the current behaviour associated with a calm emotional state is not instantly interrupted the animal would simply die. The same applies to the behaviour of the robot agent based on our emotional control model. For managing interruptions, the following rules are used in our model: if an interruption happens when emotion intensity is below the *threshold3* level the behaviour stops, otherwise the behaviour is resumed.

A latched process of emotional intensity helps the system not to get 'stuck' swapping rapidly back and forth between two emotions, thus solving a common problem in other behaviour-based architectures. There is always a delay between the expression of an artificial emotion and the initiation of a behaviour it selects. Such a delay serves two important purposes: 1) this presents a co-worker with the opportunity to infer its state and potential next action in relation to their own actions, and to adjust their work accordingly, 2) it has a role of an emotional 'memory' and makes the system more robust.

5.3 Proof of Concept

We have implemented the described emotionally-driven robot control architecture in the physical mobile robot E4, described in Chapter 3, section 3.3.1. This robot has a set of tools for sensing its environment and detecting the conditions that could trigger specific emotional states. These are the following sensors:

- Light Sensor. It outputs the intensity of detected light. This sensor is used to detect how dark is the environment. It can also be used to detect obstacles occurring in front of the sensor.
- Ultrasonic Sensor. This sensor generates sound waves and reads their echoes to detect and measure distance from objects in inches or centimetres.
- Sound Sensor. This sensor is able to measure noise levels in decibels.
- Touch Sensor. The sensor reacts to touch and release and can detect single or multiple button presses.

5.3.1 Design of Emotional States and Their Correspondence to the Environment

We have designed four emotional states: fear (ES1), surprise (ES2), happiness (ES3) and sadness (ES4). These states are associated with three emotional dimensions of valence, arousal and dominance in the way described in the Table 5.1. Mapping between dimensions of VAD and emotional states was done based on previous research discussed in Chapter 2. Each of designed emotional states was associated with an emotional intensity variable EI that could change in the range from 0 to 100. For the sake of simplicity we associated each emotional intensity variable with the same value of increase/decrease rate.

Emotional State	Valence	Arousal	Dominance
fear	-1	+1	-2
happiness	+2	+1	+1
sadness	-2	-2	-1
surprise	0	+2	0

Table 5.1: *Mapping between four designed emotional states and three emotional dimensions of valence, arousal and dominance.*

Each designed emotional state was triggered by a specific condition that could be detected by the robot in its environment.

- Condition C1: the emotional state of *fear* was triggered by the presence of a close obstacle in front of the robot. The robot was programmed to react to either any obstacle detected by its ultrasonic sensor in the distance smaller than 10 cm or an obstacle detected by its touch sensor. Such a combination of trigger and a reaction corresponds to a possible real life scenario when it should react to somebody or something that either approaches or unexpectedly appears too close to it.
- Condition C2: the emotional state of *surprise* was triggered by a sound louder or equal to 65 dB detected with its sound sensor. This is a simplification of a real life scenario when a robot should react to a sudden loud noise.
- Condition C3: the emotional state of *happiness* was triggered by the light intensity value higher than 60 on a normalized scale from 0 to 100. The light intensity was programmed to be detected with a robot's light sensor. This condition was inspired by a possible search-and-rescue scenario when a robot should find the way out of the debris.
- Condition C4: the emotional state of *sadness* was triggered by the light intensity value lower than 30 on a normalized scale from 0 to 100. The light intensity was programmed to be detected with a robot's light sensor. This was a condition opposite to the previous C3 condition and also inspired by a possible search-and-rescue scenario where a robot should avoid very dark areas.

5.3.2 Design of Emotional Expressions

As discussed earlier, each emotional state of a robot in our model should be mapped to a specific emotional expression EE and an emotionally triggered behaviour EB. We have programmed the following expressions and behaviours for the designed emotional states:

- When the emotional state of *fear* was activated the robot was programmed to immediately stop and move 5cm back. At the same time it raised its hands. Such an expression was designed based on the previous research discussed in the chapter 2. The whole chain of actions containing a stop, moving back and raising hands was called the emotional expression EE1. The emotionally triggered behaviour EB1 was inspired by a "run away" behaviour and consisted of the following robot's actions: turning 180 degree and moving forward with a high speed for 2 sec. We designed such a behaviour as a response to a fear state because it could reduce the risk of a possible damage in a real life situation and thus it logically could reduce the level of emotional intensity associated with a fear state.

- When the emotional state of *surprise* was activated the robot was programmed to immediately stop and raise its hands. Such an expression was designed based on the previous research discussed in the chapter 2. The combination of actions containing a stop and raising hands was called the emotional expression EE2. The emotionally triggered behaviour EB2 consisted of the following robot actions: turn left 90 degree, turn right 180 degree, turn back left 90 degree. We designed such a behaviour as a response to a surprise state because in a real life situation it could help a robot to collect more information about the current environment and thus reduce the risk of experiencing further unpredicted distractions.

- When the emotional state of *happiness* was activated the robot was programmed to raise its hands two times. Such an expression was designed based on the previous research discussed in the chapter 2. These actions were called the emotional expression EE3. The emotionally triggered behaviour EB3 consisted of the following robot's actions: go forward with a 1.5 times higher speed. We designed such a behaviour as a response to a happiness state because in a real life situation it could help a robot to faster reach the way out of the debris.

- When the emotional state of *sadness* was activated the robot was programmed to lower its hands. Such an expression was designed based on the previous research discussed in the chapter 2. This action was called the emotional expression EE4. The emotionally triggered behaviour EB4 consisted of the following robot's actions: go forward with a 1.5 times lower speed. We designed such a behaviour as a response to a sadness state because in a real life situation it could help a robot to approach more dangerous areas with a less risk of damage for its body.

5.3.3 The Rules of Emotional Arbitration

The rules for the emotional arbitration were the same for each emotional state / drive and were programmed as following:

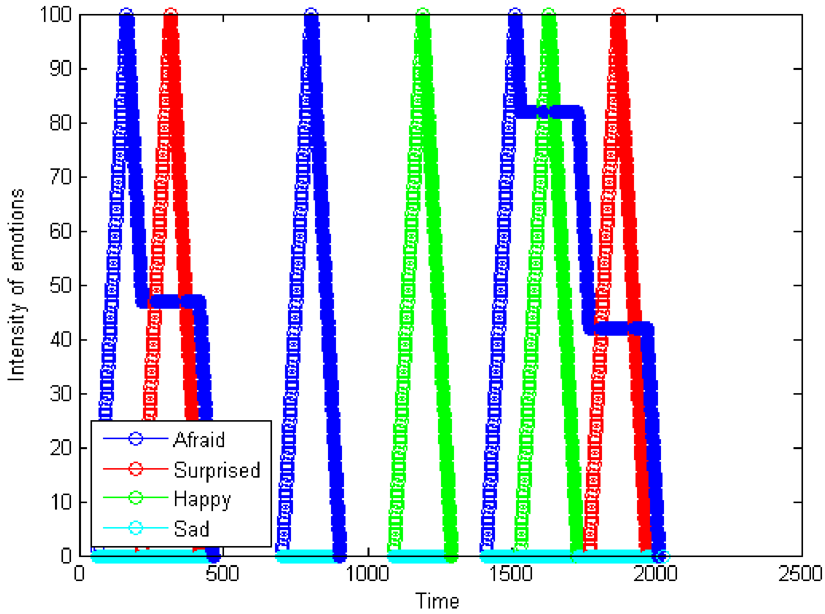


Figure 5-4: *Interruptions in emotional action selection.*

- The emotional expression EE for any emotional state ES starts when its emotional intensity EI reaches the *threshold1* level that is equal to 1.
- The emotional expression EE for any emotional state ES stops when its emotional intensity EI reaches the *threshold1* level that is equal to 100.
- The execution of the emotionally triggered behaviour EB starts when the intensity of an emotion EI reaches the *threshold3* level that is equal to 100.
- The execution of behaviour EB if not interrupted stops when intensity of the emotion EI is equal to 0.
- The interruption means that at any time moment the intensity level for the emotional state x becomes greater than the intensity level for another emotional state y, i.e. EIx > EIy.
- If an interruption happens when emotionally intensity EI for the emotional state ES is below the threshold3 the behaviour EB stops and the intensity EI is initialized to 0, otherwise the behaviour and the intensity value are paused and resumed after the interruption finishes.

The implementation of the described emotionally driven robot control model in the physical robot E4 was successful. The robot was able to detect the designed triggers. It correctly calculated in real time its internal emotional state based on the pre-programmed rules mapping the environmental triggers to the VAD values. It associated the combinations of VAD values with one of four designed emotional states or the neutral state in case no trigger was detected. The robot was able to activate the designed emotional expressions and corresponding emotionally triggered behaviours based on the calculated emotional state. It was also able to deal with the changing environment in terms of arbitrating emotional interruptions according to the pre-programmed rules discussed previously.

Figure 5-4 shows the representation of the robot's dynamically changing internal states and their intensity during the experimental test. As shown, the robot first detects the environmental change EC1 that triggers the drive of *fear*. According to the model rules, the robot performs the emotional expression EE1. While the robot is doing this, the intensity of this emotional state EI1 increases until it reaches the value of 100. After that the robot stops performing the expression EE1 and activates the behaviour EB1. The emotional intensity starts decreasing. When being at the level of 47, the robot's sensors detect another environmental change EC2 that triggers the drive of *surprise*. The robot pauses the execution of the behaviour EB1 and memorizes the EI1 value. It then increases the value of emotional intensity EI2 and performs the emotional expression EE2 until the EI2 value reaches 100. Afterwards, the robot activates the behaviour EB2 and decreases EI2 until 0. When the *surprise* interruption is over, the robot resumes the previously paused behaviour EB1 and continues to decrease the intensity EI1 from the memorized value of 47 until 0.

5.4 Discussion and Conclusion

In this chapter we presented an emotionally based computational model of action selection to control robot behaviour in human-robot interaction scenarios. We have implemented the described model as a proof of concept. The physical robot E4 with an implemented model has successfully interacted with the environment and was able to express its internal emotional state and to change its behaviour dynamically according to the implemented actions' interruptions scheme.

However, the presented model of emotional action selection raises several design-related concerns that need more research. First, it is not clear what should be the relation between the discrete emotional state and the emotional dimensions of valence, arousal and dominance. When designing the robot's behaviour it could be obvious for the designer that the robot's expression should be e.g. highly positive or the robot should be highly aroused in response to some conditions. But it is not always obvious what emotional state should be associated with the desired dimensional value. Further research is needed to understand and clarify the relation between the three emotional dimensions and the discrete emotions.

Secondly, it still is an open question in the up-to-date HRI research how to design the emotional expressions in robots that would be understandable by human observers. There exist many studies that focus on human-like facial expressions that help represent various emotional states in robots but more research is needed in the area of emotionally expressive body language in robots, especially non-humanoid.

It is also important to understand what effect could the situational context have on the perception of robot behaviour. When designing robot emotional expressions and actions, it is important to know whether its behaviour could override the impression brought by environmental context or not.

In further chapters we will investigate and discuss in more details the design and implementation issues associated with the model of emotional action selection in robots for the purpose of human-robot interaction. In Chapter 6 we will present a design scheme for modelling emotionally expressive robot body movements. It will inspect the relation between several discrete basic emotions and the emotional dimensions of valence, arousal and dominance. In addition, we will present and study a set of design parameters that enable the creation of emotionally expressive behaviours.

In Chapter 7 we will investigate and discuss the effect of situational context on interpreting emotional robot body movements from the human observer's point of view. In Chapter 8 we present the concept of emotional expressivity in robots and validate the previously presented design scheme for modelling emotionally expressive robot body movements on two physical robots of different expressivity.

CHAPTER 6

DESIGN SCHEME FOR MODELING EMOTIONALLY EXPRESSIVE ROBOT BODY MOVEMENTS

6.1 Introduction

In the previous chapter we presented a plausible emotionally-based computational model of action selection to control robot behaviour in human-robot interaction scenarios. The physical robot with the implemented model has successfully interacted with the environment and performed the programmed actions and expressions. In the real life human-robot interaction scenarios robots not only interact with the environment but also with the surrounding people. Robots are going to work together with people in human-robot teams in the future. In order to work successfully as a team, the members of that team should have a certain level of mutual understanding. Each team member should be able to understand the current status of the other team members: is (s)he successful in what (s)he is doing, does (s)he need help, what his/her intentions are. In human teams, this knowledge often comes from social communication and specific non-verbal behavioural cues, such as emotional expressions. However, in human-robot teams there is a lack of such a communication.

This chapter presents a design scheme for expressing artificial emotional states in non-humanoid robots and thus addresses the second research question outlined in the Chapter 1 and formulated as “RQ2. Can robotic bodily expressions be generated and emotionally charged in a systematic pre-structured manner to evoke a desired emotional interpretation?” This chapter focuses on creating a system for designing a specific robotic body language that could help humans to better understand robot states and intentions in different situations that could occur in a simple working environment.

Previous studies have shown that people can understand emotional states expressed by robots using facial expressions [76, 154]. Less research has been conducted on the possibility of expressing robotic emotions with sounds [140] and body language [15, 74] in humanoid robots. However, very little prior work has addressed the opportunities and challenges of creating an emotionally expressive body language for non-humanoid robots [165], as discussed in Chapter 2, section 2.3.3.

In this chapter we focus on emotional body language for non-humanoid robots. We propose a design scheme for modelling emotionally expressive robotic movements. We hypothesize that expressions designed according to the scheme help people recognize five basic emotions implemented in a non-humanoid robot with a better-than-chance recognition level. Previous psychological studies have suggested that the discrete model of basic emotions is not always enough to explain all the complicated nature of an emotional experience [40]. The dimensional approach has been argued to encompass a greater degree of subtlety that supports interpretation of emotional states [40]. In HRI research, a dimensional approach is often used as well for mapping emotional robot expressions to a specific internal state [153], as discussed in more detail in Chapter 3, section 3.4.1. In our study we also assume that basic emotions could not explain the whole image of how people see and understand robots. Thus we decided to additionally analyse whether our proposed scheme shows any relation between the parameters implemented in a robot and perceived emotional dimensions of valence, arousal and dominance. In order to investigate whether robotic bodily expressions generated using the proposed design scheme evoke a desired emotional interpretation, we implement the dynamic expressions of five basic emotions of *fear, anger, happiness, sadness* and *surprise* into a non-humanoid robot E4 and ask people to recognize the implemented expressions in our study. The results of the study show that the accuracy of recognition is high for all the emotions, mostly due to a high level of recognition specificity and a high number of true negatives. The values of recognition ratio exceed the chance level for four recognized emotions of *fear, anger, happiness* and *surprise.* The recognition ratio of *sadness* is below the chance level in this study, which suggest that the static posture may represent sadness better than a dynamic expression. The robot expressions of *anger* and *fear* are sometimes misclassified as *surprise*, while the expression of *surprise* is most often misclassified as *fear* and the expression of *happiness* is sometimes misclassified as *anger.* Such errors suggest that some design parameters do not communicate the full emotional information a specific discrete emotion includes, but rather provide observers with the information useful to better detect one emotional dimension and give less information about another dimension. In general, the results show that the parameters of our suggested model are related to the perceived level of valence, arousal and dominance. Thus, our model can be used by HRI researchers as a basis for implementing a set of emotions in non-humanoid robots.

As a second focus of the study we present the analysis of the human observers' perception of a robot performing emotionally charged movements according to the presented scheme. Human perception is measured using a part of the Godspeed questionnaire that consists of perceived anthropomorphism, animacy, likeability and perceived intelligence of a robot. This addresses the fourth research question formulated as “RQ4: What are the effects of robotic emotional bodily expressions on people’s attitude towards a robot?” The results of the study presented in this chapter demonstrate that people perceive emotionally expressive robots as more anthropomorphic, more animate and even more likeable. Specifically, in terms of Anthropomorphism, emotional robots expressing any of five basic emotions of *fear, anger, happiness, sadness* or *surprise* are perceived as being more natural, more humanlike and more conscious. In terms of perceived Animacy of the robots expressing these five emotions, emotional robots are rated as more organic, lifelike and responsive comparing to non-emotional. In terms of Likeability, emotional robots expressing *fear, happiness, sadness* or *surprise* are perceived as more pleasant and being liked more than non-emotional. In addition, the results of the study reveal that robots are perceived as more responsible when they express the emotions of *anger* or *surprise*. And finally, emotional robots expressing any of five basic emotions of *fear, anger, happiness, sadness* or *surprise* are perceived as being more intelligent. The results of this research suggest that, in a context of a joint human-robot activity, emotionally expressive robots will be able to better engage people in interaction. The enhanced attitude towards emotionally expressive robots could create a higher level of empathy between people and robots and thus improve social coordination between them for the purpose of a better collaboration.

The scheme presented in our study is an important step in HRI research as it is expected to give other researchers a general design system for fast and easy creation of recognizable emotional expressions in different types of non-humanoid robots.

6.2 Approach

The expressive behaviours that have been programmed into the robot have been computationally modelled as a simplification of what is known about behaviours that are associated with human and animal emotions. The critical aspect of a robotic emotional signalling system is that the behaviours it generates must be well matched to what is familiar to people. This approach is intended to make a robot’s behaviour accessible to the intuitions of a person who observes it. Thus our study focused on perhaps the most fundamental behavioural form of approach-avoidance, which is considered to be a set of universal movements of all animals [8]. Numerous studies have linked approach-avoidance motivations to emotional characteristics [75].

In our study, both approach and avoidance behaviours were analysed from the perspective of robot observer. In addition, we employed Laban’s body expression theory [93]. Labanian theory, also used in HRI studies [161], classifies elements of expression contained in a body movement into two categories named Shape and Effort, where Shape is a feature that concerns overall posture and movement, while Effort is defined as a quality of the movement.

In order to define the Shape of emotional robot movements, we linked the emotional expression to a more general 'goal' of the expressive robot of either becoming closer to an observer by moving closer or becoming bigger without moving closer, as presented in the Figure 6-1. These two groups of movements although very different by their nature could both fulfil the purpose of a perspective approach from the observer's point of view and thus communicate a certain emotional cue. In order to generalize the framework of emotional expressions to different types of robots, we linked each possible movement to a specific part of a body in accordance with anatomical body planes that could be applied to both humanoid and non-humanoid bodies. Different features of Shape are organized hierarchically in Figure 6-1, with the highest level of abstraction on the left and the lowest - on the right. The lowest level of abstraction is a specific emotion associated with higher levels. The emotions are linked to higher level parameters based on previous research in human body language [15, 44, 85, 41, 180].

Although Laban's theory describes quality of movement as a matter of dance effort, in the context of HRI the term *Quality* is used to capture dynamics of an expressive movement. Quality is divided into three subcategories: energy (strength of the movement), intensity (suddenness), and a flow/regularity category, which is itself subdivided into the duration of the movement, changes in tempo, frequency and trajectory of the movement. Figure 6-2 presents these subcategories as a part of the whole modelling system. Different features representing Quality of the movement are organized in the same hierarchical nature in Figure 6-2, as *Shape* categories. The emotions on the lowest level are linked to higher level parameters based on previous research in human body language [74, 44, 85].

6.3 Method

We have been experimenting with the same E4 robot that was presented in Chapter 3, section 3.3.1. The following robot's construction features were important for the study described in this chapter: the robot had two motors that allowed it 1) to move forward and/or backwards on the surface, 2) to move its upper body part. The upper body part was constructed in such a way that the robot's hands were connected and moved together with robot's neck and eyebrows. Neck could move forward / backwards, hands could move up and down, and eyebrows could also rise up and down. These features allowed us to experiment with alternative values for parameters of Shape and Quality.

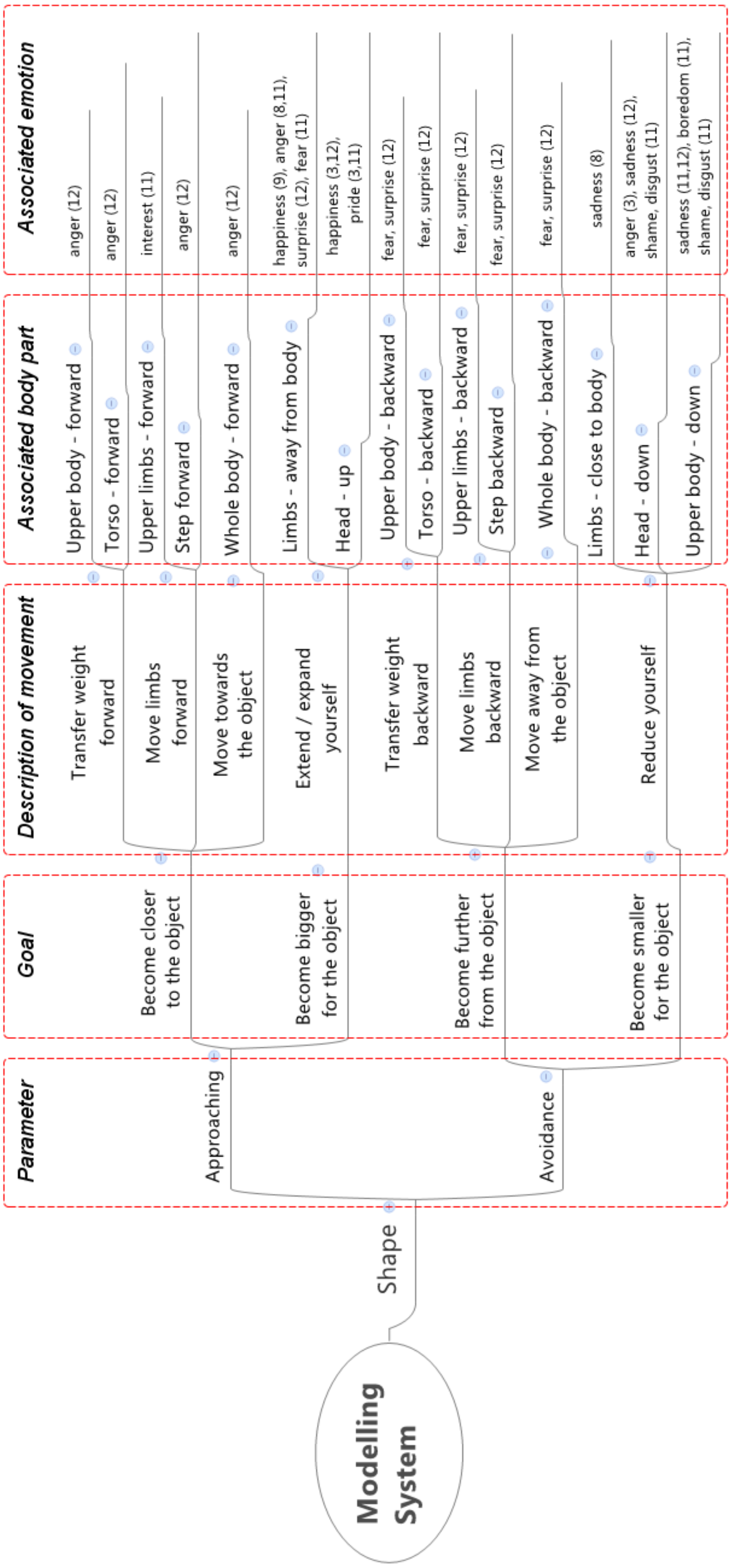


Figure 6-1: *Shape as a category of the emotional modelling system.*

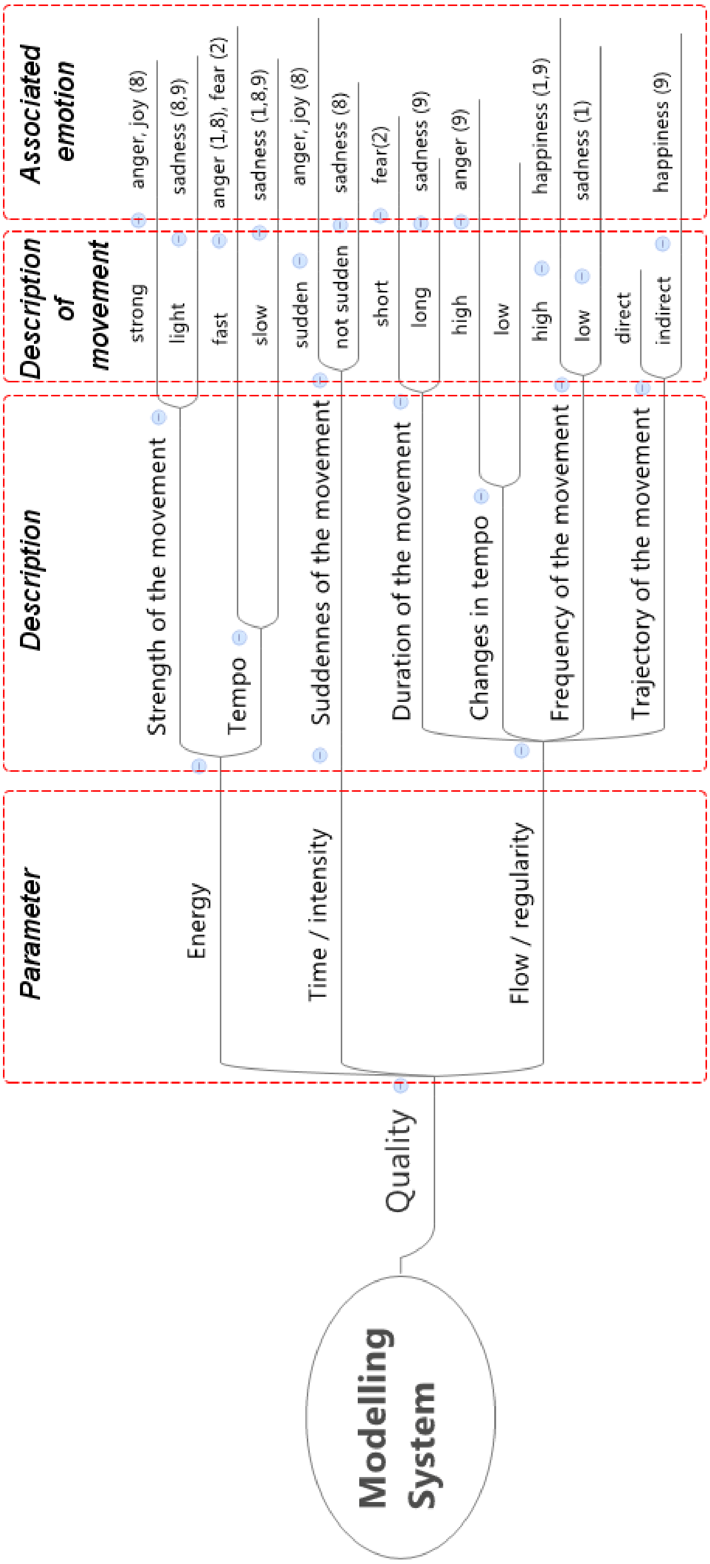


Figure 6-2: *Quality as a category of the emotional modelling system.*

6.3.1 Use of the Scheme for Expressing Basic Emotions

In the study we designed five emotional expressions of fear, anger, happiness, sadness and surprise. Figure 6-3 presents several screenshots of the expression of *fear*, which was designed as follows: 1) The robot suddenly stops in front of the obstacle. This corresponds to the design parameter of high Intensity (suddenness of the movement). 2) The robot moves its upper body backward. This movement corresponds to both a parameter of Avoidance (transfer weight backward) and high Frequency. 3) The robot moves backwards away from the obstacle with a high speed. This movements is associated with the parameters of Avoidance (move the body backward)and high Energy (tempo), as described in Section 2.2.3.

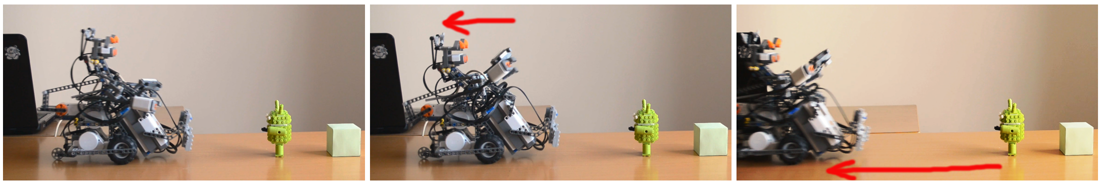


Figure 6-3: *Emotion of fear expressed by the robot E-4*

Figure 6-4 presents several screenshots of the expression of *anger*, which was designed as follows: 1) The robot stops in front of the obstacle and suddenly moves its head forward towards it. Such a movement is associated with both high Intensity (suddenness of the movement) and Approach (move upper body forward). 2) The robot moves closer to the obstacle with the higher than normal speed. These correspond to Approach (move towards the object) and high Energy (tempo). 3) The robot suddenly stops close to the obstacle and again moves its head forward towards it. These correspond to high Intensity (suddenness) and Approach again, as described in Section 2.2.3.

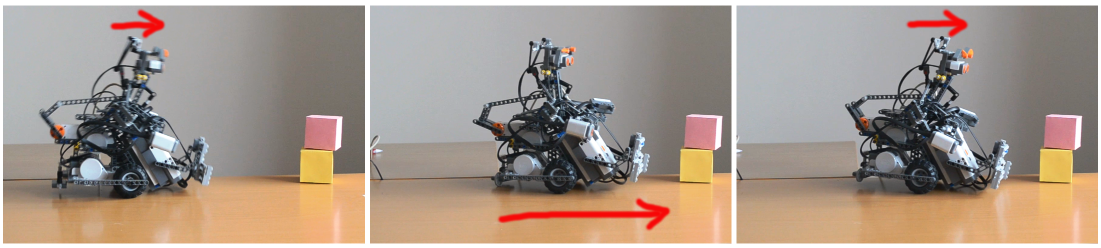


Figure 6-4: *Emotion of anger expressed by the robot E-4*

Figure 6-5 presents several screenshots of the expression of *happiness*, which was designed as follows: 1) after finishing its task the robot shortly raises its hands and its eyebrows once, 2) the robot moves forward towards the observer and stops after some time, 3) then it shortly raises its hands and eyebrows one more time. The expressed movements correspond to the parameters of Approach, such as Moving limbs away from the body and high Frequency, as described in Section 2.2.3.

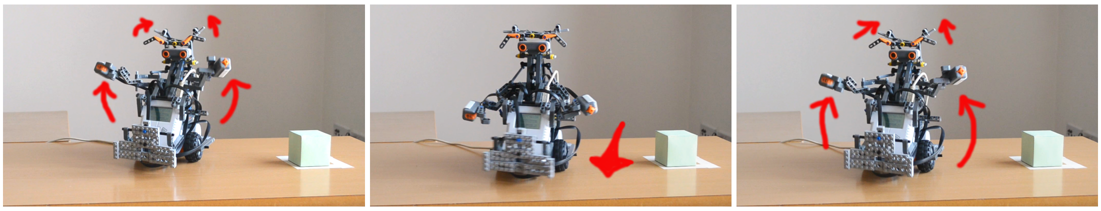


Figure 6-5: *Emotion of happiness expressed by the robot E-4*

Figure 6-6 presents several screenshots of the expression of *sadness*, which was designed as follows: 1) the robot smoothly stops in front of the obstacle, 2) it slowly turns towards the observer, 3) it slowly moves towards the observer with its eyebrows down. The expressed movements correspond to the Quality parameters only, such as low Intensity (not sudden movements), low Frequency, and low Energy resulting from light Strength of the movement and slow Tempo, as described in Section 2.2.3.

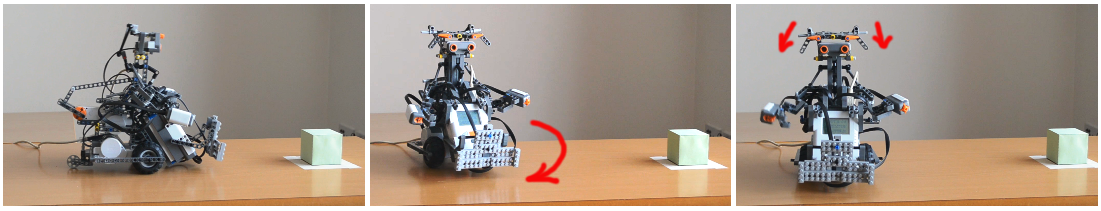


Figure 6-6: *Emotion of sadness expressed by the robot E-4*

Figure 6-7 presents several screenshots of the expression of *surprise*, which was designed as follows: 1) the robots suddenly stops after the obstacle falls down in front of it, 2) immediately after, the robot moves its upper body backward. The expressed movements correspond to the parameters of high Intensity (sudden stop) and Avoidance (upper body backward) as described in Section 2.2.3.

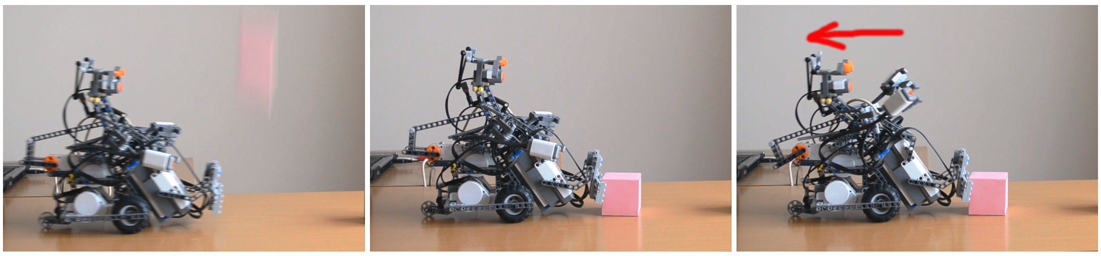


Figure 6-7: *Emotion of surprise expressed by the robot E-4*

The movement features used to create five emotional expressions of the E4 robot inform our design scheme compounding twenty-three design parameters of expressive *Shape* and *Quality*, that will be presented later in Chapter 8, Table 8.1. In the updated and improved design scheme, presented in Table 8.1, all the movement features that define how the overall posture of a robot changes in terms of its physical form, correspond to the design parameters of expressive *Shape*. All the performative characteristics of robot movement, such as strength or frequency, correspond there to the design parameters of expressive *Quality*.

6.3.2 Measures to Evaluate Recognition of Emotional Expressions

The independent variable of this study is the emotional expression presented by the robot. In our study we used five emotional expressions: afraid, angry, happy, sad and surprised. We also implemented a control expression with no emotion when a robot does not react affectively to a change of the environment. The dependent variable was an emotional term, selected by participants and based on their recognition of the expressed emotion. We offered participants seven terms to select from: afraid, angry, happy, sad, surprised, not emotional, other. The measure used to obtain results for this research question was the recognition ratio $r(p_i, e_j)$ for each expression, which was calculated as defined by Eq. 6.1.

$$r(p_i, e_j) = \frac{N_{ij}}{N} \tag{6.1}$$

where:
p_i = expression number i ,
e_j = selected emotional code number j;
N_{ij} = number of responses (p_i, e_j);
N = total number of responses.

In order to evaluate in more details the results of expressions recognition by participants, we additionally calculated the values of true positives, true negatives, false positives, false negatives, Accuracy, Recall, Precision, Specificity and F-score for each expression. True positives (TP) are cases in which the participants recognized the presented robot's emotional expression with the same label as the expression was designed to present, e.g. the expression of *fear* was recognized as *fear*. True negatives (TN) were calculated as the number of cases when the robot was not expressing a particular emotion and the participants did not recognize it as that particular emotion, e.g. any expression of the robot which was *not fear* was recognized as *not fear*. False positives (FP or Type I error) are the cases when participants recognized as a particular emotion the one which was not actually presented to them, e.g. the expression of *not fear* was recognized as *fear*. False negatives (FN or Type II error) are the cases when the participants were presented with a particular emotion but did not recognize it correctly, e.g. the robot's expression of *fear* was recognized as *not fear*.

The four values of TP, TN, FP and FN let calculate several rates that are often used for evaluating the ability to correctly recognize presented input, in our case - presented emotional expression of the robot. Accuracy is the term most often used for evaluating the correctness of classification. It shows how often, overall, participants were correct in

	Recognized: NO	Recognized: YES	
Presented: NO	TN	FP (Type I error)	**Specificity** $= \frac{\sum TN}{\sum Presented{:}NO}$
Presented: YES	FN (Type II error)	TP	**Recall** $= \frac{\sum TP}{\sum Presented{:}YES}$
		Precision $= \frac{\sum TP}{\sum Recognized{:}YES}$	**Accuracy** $= \frac{\sum TP + \sum TN}{Total}$

Table 6.1: *Calculating Specificity, Recall, Precision and Accuracy using true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN).*

recognizing robot's emotional expressions. Accuracy is often associated with systematic errors, while Precision is associated with random errors. Precision shows how often a specific emotion was correctly recognized when presented to participants through a robot's expression. Recall, otherwise called True Positive Rate or Sensitivity, relates to the ability of participants to correctly detect emotions expressed by the robot. In other words, Recall shows how often the emotion is recognized correctly when presented through the robot's expression. Specificity relates to the ability of participants to correctly detect that the particular emotion was not presented to them through a robot's expression. Specificity is a proportion of cases when participants recognized the particular emotion as not present and it was not actually presented. The Table 6.1 presents an overview of how all the terms are calculated and related to one another.

The final value used to measure the accuracy of recognition is the F-score (F_1). It considers both the precision and the recall to compute the score and is called a *harmonic mean* of them both. F-score is useful as it is a single measure that allow comparing the results of different tests. F-score is calculated as defined by Eq. 6.2.

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{6.2}$$

6.3.3 Model's Parameters and Emotional Dimensions

We used an experimental study to investigate the causal relations between the parameters of affective robotic expressions and a perceived emotional dimension. We focused on a subset of the parameters of the model were implemented in our experiment. We implemented the following parameters in five affective expressions and one neutral:

1. Approach/avoidance parameter. This parameter was not used for the expression of sadness.

2. Energy/speed parameter, defined as an average power of robot's motors per expression, where 100 (%) is a maximum.

EmotionID	Approach / Avoidance	Energy	Intensity	Duration, sec	Frequency
1 (fear)	Avoidance	100	1	0.63	1.59
2 (anger)	Approach	75	1	2.58	0.78
3 (happiness)	Approach	67	1	3.33	0.60
4 (sadness)	mixed (not used)	27	0	12.0	0.17
5 (surprise)	Avoidance	75	1	1.0	1.00
6 (not emotional)	Neither	0	0	0.0	0.00

Table 6.2: *Defining the main parameters of the framework.*

EmotionID	Description	Valence / Pleasure	Arousal	Dominance
1	afraid	-1	+1	-2
2	angry	-1	+1	+2
3	happy	+2	+1	+1
4	sad	-2	-2	-1
5	surprised	0	+2	0
6	not emotional	0	0	0

Table 6.3: *Mapping between discrete emotions and three emotional dimensions.*

3. Time/intensity parameter, defined as +1 when robot's expressive movements were programmed as sudden (Motors.SmoothStart = false) , and as 0 when the movements were programmed as smooth (Motors.SmoothStart = true).

4. Flow/regularity parameter, consisted of two sub-parameters:

   (a) Duration of the expression

   (b) Frequency of movement, defined as Number of hands' movements / Duration

For each of the expressions the values of parameters presented in Table 6.2 were used as independent variables.

The values of recognized valence, arousal and dominance were used as dependent variables in our study. We used a Mehrabian model of emotions [108] to present five basic discrete emotions used in our study to a three-dimensional pleasure-arousal-dominance (PAD) space. We decided to use the PAD model firstly because it is often used to measure the affective value of facial expressions, and second because there was a validated questionnaire available.

The mapping between discrete emotions and the three dimensions was conducted based on previous studies in behavioural and experimental psychology [27, 73] and is presented in the Table 6.3. We scaled the values of all three dimensions to a 5-point scale [-2, 2] in order to proportion it to a 5-step Self-Assessment Manikin tool [20] we used for measuring participants' perception.

Dimension of a context	Positive	Negative	Neutral
Valence	Something positive happens, e.g. robot finishes its task successfully.	Something negative happens due to e.g. robot's fault.	Nothing happens.
Arousal	Something sudden happens in the environment.	Nothing happens in the environment, robot's help isn't needed.	Nothing happens.
Dominance	Robot has no power to handle a situation as something dangerous prevents it from completing a task, e.g. a big obstacle.	Robot has a power to handle a situation as something harmless prevents it from completing a task, e.g. a small obstacle.	Nothing happens.

Table 6.4: *Dimensional approach for creating a context for robot emotional expressions.*

Context	Recorded emotional expression
Valence positive / negative	Happy, angry, neutral
Arousal positive / negative	Sad, surprised, neutral
Dominance positive / negative	Angry, afraid, neutral
Neutral	Afraid, angry, happy, sad, surprised

Table 6.5: *A list of emotional expressions, presented to participants.*

6.3.4 Creating Context

In order to analyse the effect of presented situational context on participants' perception of emotions we created several contexts for each expression. We used the same three-dimensional approach for creating a context for robot emotional expressions, as described in Table 6.4 .

As a result, we recorded a set of videos where each context was combined with a specific emotional expression of the same and the opposite level of the appropriate dimension. As a consequence, we got a list of twenty three emotional expressions of the robot in different contexts, as described in Table 6.5, each of the duration of about 5 sec.

In this chapter, we only discuss the results of the emotional expressions performed within an appropriate context, e.g. expression of happiness performed in the context of positive valence or expression of sadness performed in the context of low arousal. All the details about other combinations of context and expression, as well as the impact of the context on the perception of expressed emotions, will be discussed in the Chapter 7.

6.3.5 Measuring the Attitudes Towards the Robot

In order to measure the observers' attitudes towards the robot we used the Godspeed Questionnaire Series [12], which consists of a series of 5-point Likert scales. We used this tool in our study because first of all, it lets perform the measurements of several key concepts in HRI, such as anthropomorphism, animacy, likeability and perceived intelligence. These concepts are both a good general indicator of human attitudes towards an emotional robot and also are capable of providing more detailed view on the attitudes by e.g. going deeper from the concept of likeability to being friendly or pleasant. Another important reason for using this questionnaire was its reliability and validity [12]. Last but not the least was the fact that this questionnaire is widely used in HRI research [50, 65, 92] and thus it allows to compare the results of our study with the work of others.

The four concepts included in the part of the questionnaire we are using in our study, are: Anthropomorphism, Animacy, Likeability and Perceived Intelligence.

Anthropomorphism refers to the attribution of a human form, human characteristics, or human behaviour to non-human things such as robots. The scales included into this part of the questionnaire are the following:

- Fake - Natural
- Machinelike - Humanlike
- Unconscious - Conscious

Animacy refers to the concept of making the robots lifelike and "sort of alive" [173]. The scales included into this part of the questionnaire are the following:

- Mechanical - Organic
- Artificial - Lifelike
- Apathetic - Responsive

Likeability refers to the level of a positive impression made by the robot. It has been reported that positive first impressions of a person often lead to more positive evaluations of that person [148], thus the positive impression of the robot may lead to a more effective teamwork between the robot and the human. The scales included into this part of the questionnaire are the following:

- Dislike - Like
- Unpleasant - Pleasant

Finally, the *Perceived Intelligence* concept is coping with the ability of the robot to produce a behaviour which is perceived as intelligent to human observers. The scales included into this part of the questionnaire are the following:

- Irresponsible - Responsible
- Unintelligent - Intelligent
- Foolish - Sensible

6.3.6 Procedure

A within-subject design was used to assign participants to a specific task condition, i.e. each participant was exposed to all the experimental conditions. In order to overcome limitations of a within-subject design and decrease the impact of a learning effect, the videos presented to each participant were randomized. We randomized the conditions and ensured the two expressions of the same emotion were never presented one after another.

Participants were initially given a questionnaire containing demographic questions about age and gender. The participants were asked to sit on a chair at the table in a quiet room, watch the recorded videos and after each of them answer the questions from the prepared paper-based questionnaire (see Appendix C). The questionnaire contained a Self-Assessment Manikin tool [20] and a forced-choice question regarding the perceived emotion of the robot. In order to produce reliable results we tried to eliminate control biases that could appear during the experiment. In order to control biases, we prepared a written document with detailed instructions for participants (see Appendix B) and ran a pilot study before actual data collection to identify potential biases. In order to control biases caused by participants, we reassured the participants that we were testing the robot's behaviour, not them.

The experimenter stayed neutral while supervising experiments thus reducing the chance to intentionally or unintentionally influence the experiment results. We controlled environment-introduced biases by making the experimental room without notable distractions. The participant was seated alone at the table and the experimenter was seating in another corner of the room in case the participant would need any help. The duration of the experiment did not exceed thirty minutes.

One-way repeated measures ANOVA was used as a statistical test for evaluating the relation between each parameter and a perceived emotional dimension. The G*Power tool [1] was used to compute statistical power analyses for this test and an a priori calculation of a required sample size showed the need of 33 participants for our within-subject study in order to have an Effect size f= 0.3 (where α err prob=0.05, Power (1-β err prob)=0.95, Number of groups = 3).

[1] http://www.gpower.hhu.de/en.html

6.4 Results

34 people (10 females and 24 males) agreed to participate in a study, ranging in age from 18 to 46 (M=23.21, SD=7.42).

6.4.1 Correctness and Consistency of Recognition

In this section, we are going to present the recognition results for the expressions presented by the robot within an appropriate situational context. The results demonstrate that the emotions of fear, anger, happiness and surprise are recognized on a better-than-chance level when implemented according to the proposed framework.

The tabular presentation of true positives, true negatives, false positives, false negatives, Accuracy, Recall, Precision, Specificity and F-score values for each presented emotional expression are given in the Table 6.6.

	TP	TN	FP	FN	Accuracy	Recall	Precision	Specificity	F-score
fear	19	160	9	15	0.88	0.56	0.68	0.95	0.61
anger	35	132	3	33	0.82	0.51	0.92	0.98	0.66
happiness	32	160	9	2	0.95	0.94	0.78	0.95	0.85
sadness	4	163	7	29	0.82	0.12	0.36	0.96	0.18
surprise	29	127	42	5	0.77	0.85	0.41	0.75	0.55

Table 6.6: *The tabular presentation of true positives, true negatives, false positives, false negatives, Accuracy, Recall, Precision, Specificity and F-score values for each presented robot emotional expression.*

Overall, the Accuracy of recognition was high for all the emotions, ranging between the lowest 77% value for *surprise* and the highest 95% value for *happiness*. According to the results, such a high Accuracy was mostly due to a high level of recognition's Specificity. The table shows that the number of true negatives for all the presented expressions was high and this resulted in high levels of Specificity that reached 75% for *surprise* and ranged between 95-98% for other emotions. Other measures, such as Recall and precision are more varied comparing to Accuracy and Specificity. The highest Recall rates were detected for *happiness* as 94% and for *surprise* as 85%, showing the ability of participants to correctly recognize these two emotions presented to them through emotional expressions of the robot. *Fear* and *anger* both had very similar Recall rates of 56% and 51% respectively. The lowest recall rate was detected for *sadness* and was as low as 12%. The Precision values were spread similarly to Recall rates. The highest Precision was detected for *anger* (92%) and *happiness* (78%), while the lowest values decreased to 41% for *surprise* and 36% for *sadness*.

The combination of Precision and Recall is another important measure that characterizes how correctly participants were recognizing emotional expressions of the robot presented to them. The diagram on the left part of Figure 6-8 shows that *happiness* and *fear* are the two most balanced emotions in terms of the values of Recall and Precision detected when recognized them by participants. Both *sadness* and *anger* have higher Precision than Recall. In case of *surprise*, Recall rate was higher than Precision. The combination of these two values, calculated as F-score, are presented on the right part of the Figure 6-8, showing the highest F-score value for *happiness* and the lowest score for *sadness*.

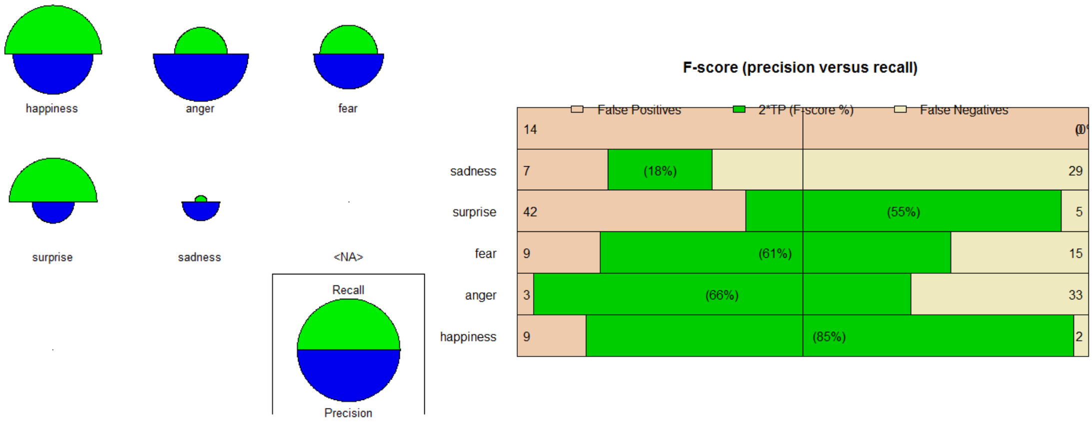


Figure 6-8: *Left: the combination of Precision and Recall for each presented emotion. Right: the F-score values for each presented emotion.*

The confusion matrix given in Figure 6-9 presents the percentages of recognition ratio for each robot emotional expression shown to participants. Each row of the matrix represents the shown emotional expression of a robot, while each column represents the emotion as it was recognized by participants. The cells of the matrix are coloured so that the greener cells show the higher percent of recognition, while the grey cells show the lower percent of recognition. The cells with a red border represent the correctly recognized emotions. This confusion matrix shows that the recognition ratio for such emotions as surprise and happiness were the highest and reached 85.3% and 94.1% respectively. The expressions of anger and fear have very similar recognition ratios of 51.5% and 55.9% respectively. The lowest recognition ratio was for the emotion of sadness, 12.1% only.

The confusion matrix shows that although the expression of *surprise* has a high recognition ratio of 85%, other expressions, such as *sadness, anger* or *fear* were also quite often recognized as *surprise*. This results in a lower F-score of *surprise*, as previously discussed. The expression of *sadness* that had the lowest recognition ratio of 12% was very often misclassified. The most common misclassification for *sadness* was *surprise* (42.4%). However, *sadness* was also misclassified as *fear* (6.1%), *anger* (3%) and other emotions, even *happiness* (9.1%).

To measure a certain level of agreement between the users the Fleiss' κ statistical measure was used. The Fleiss' κ value calculated based on the results of expressions' recognition showed the substantial agreement for the emotion recognized as *happiness*

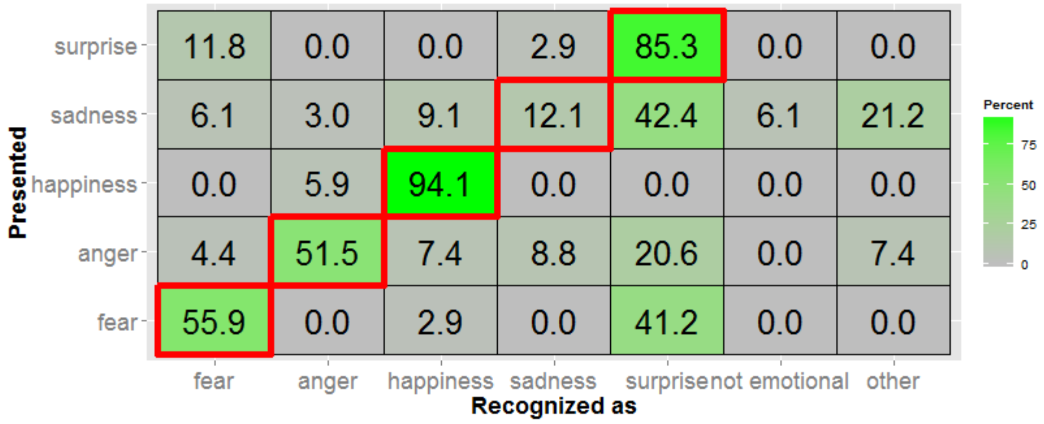


Figure 6-9: *Confusion matrix*

and the moderate agreement for the emotion recognized as *surprise*. Robot emotions of *fear* and *anger* were interpreted with a fair agreement. And finally, the emotion interpreted as *sadness* had only a slight agreement, as shown in Table 6.7.

Emotional Description	Fleiss' κ value	Interpretation of κ value
Fear	0.33	Fair agreement
Anger	0.37	Fair agreement
Happiness	0.79	Substantial agreement
Sadness	0.04	Slight agreement
Surprise	0.42	Moderate agreement

Table 6.7: *Participants' agreement regarding the E4 robot's emotional bodily expressions.*

The overall agreement between the participants on the four emotions of *fear, anger, happiness* and *surprise* was on the moderate level, with overall the κ value of 0.47 and $p < 0.0001$.

6.4.2 Modelling Parameters: Approach and Avoidance

In order to get more insights of why one emotions were misclassified as others, we investigated a relation between different design parameters and values of perceived valence, arousal and dominance. In this section, we present a relation between the parameters of Approach and Avoidance and the three perceived emotional dimensions. When designing emotional expressions, we used the parameter of Avoidance for the expressions of *fear* and *surprise* and the parameter of Approach for the expressions of *anger* and *happiness*. It may be possible that the design parameters do not directly encode an emotional state but rather influence the perception of specific emotional dimensions, such as dominance or arousal. For example, the use of both Approach and Avoidance may influence a high perceived arousal and thus explain misclassification

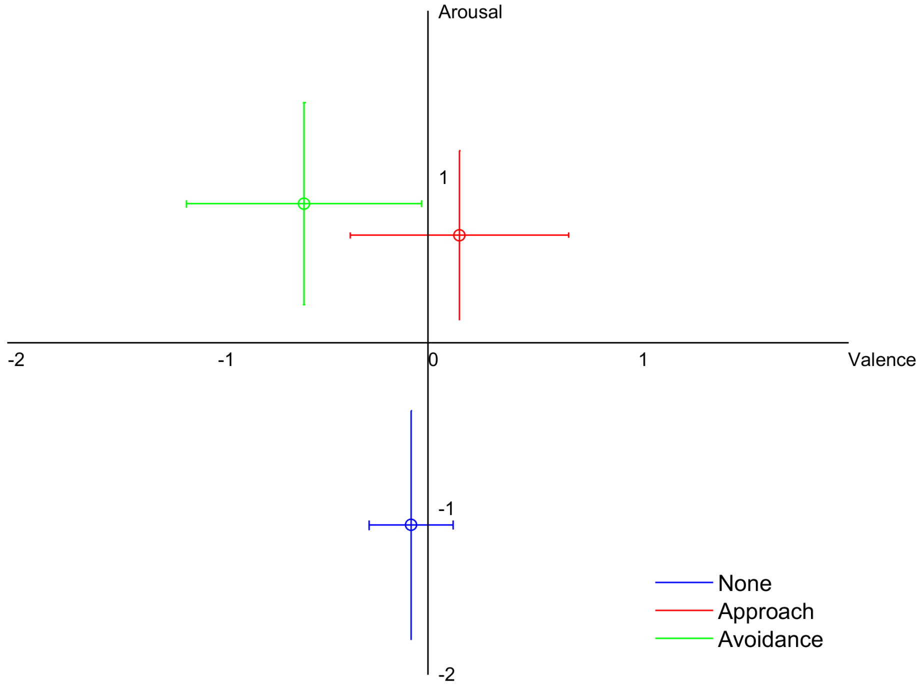
	Valence		Arousal		Dominance	
	Mean	StDev.	Mean	StDev.	Mean	StDev.
Approach	0.15	0.52	0.65	0.51	0.05	0.41
Avoidance	-0.59	0.56	0.84	0.61	-0.22	0.47
neither Approach nor Avoidance	-0.08	0.20	-1.10	0.69	-0.11	0.58
low Energy	-0.44	0.50	-0.07	0.66	-0.26	0.62
medium Energy	0.03	0.67	0.66	0.52	0.09	0.42
high Energy	-0.22	0.61	0.99	0.67	-0.63	0.76
low Intensity	-0.13	0.23	-0.77	0.52	-0.16	0.42
high Intensity	-0.17	0.49	0.73	0.50	-0.07	0.35
short Duration	-0.44	0.50	0.72	0.62	-0.47	0.52
medium Duration	0.03	0.67	0.74	0.57	0.22	0.51
long Duration	-0.22	0.61	-0.07	0.66	-0.26	0.62
low Frequency	-0.22	0.61	-0.07	0.66	-0.26	0.62
medium Frequency	-0.01	0.56	0.66	0.52	0.09	0.42
high Frequency	-0.75	0.69	0.99	0.67	-0.63	0.76

Table 6.8: *Mean values and standard deviation values of perceived valence, arousal and dominance for different parameters of emotional robot expressions.*

between certain emotional expressions. On the other hand, the use of Approach may result in a high perceived dominance, while the use of Avoidance may result in a low perceived dominance. Thus, this design parameter may help differentiate between certain emotional expressions. The results presented in this section explain that there are very few misclassification between the emotions of happiness or anger because both of them include the design parameter of Approach. The same is true for the emotions of fear and surprise as they both include Avoidance.

We used a repeated measures ANOVA test for investigating a relation between different parameters of emotional robot expressions and a value of perceived valence, arousal and dominance. The results of the test for all the tested design parameters are presented in the Table 6.8.

The repeated measures ANOVA test with a Greenhouse-Geisser correction did not reveal any significant difference between the perception of arousal, although both approach and avoidance significantly ($p < 0.0005$) raised the perceived level of arousal comparing to a neutral robot expression. Mean scores of valence differed significantly between a neutral expression, approach and avoidance ($F(1.74,57.49) = 32.399$, $p < 0.0005$). The mean score of valence for the expression of avoidance was negative and was significantly lower ($p < 0.0005$) comparing it to a positive mean of valence for approach or to a neutral expression. Mean scores of dominance also differed significantly between a neutral expression, approach and avoidance ($F(1.75,57.68) = 3.76$, $p = 0.035$). Approach expressions determined a significantly higher positive value of a perception of dominance, while avoidance resulted in a significantly lower negative value of dominance ($p = 0.011$).



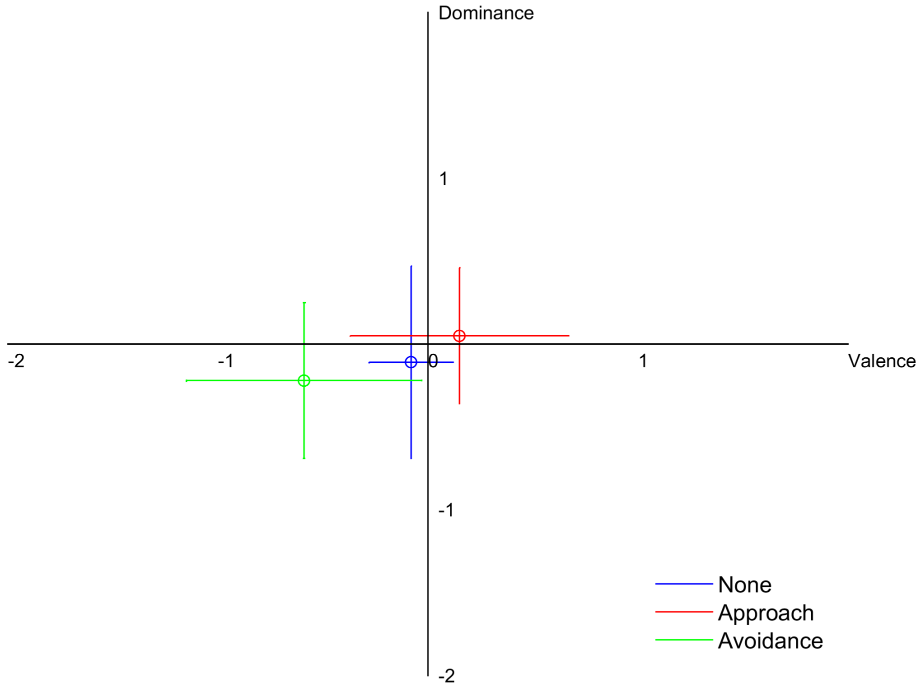


Figure 6-10: *Plots of the Mean values and Standard Deviation of the ratings for the emotional expressions containing approach, avoidance and neither approach, nor avoidance*

These findings help explain why there was very few misclassification between the emotions of *happiness* or *anger*, both of which included the design parameter of Approach, and the emotions of *fear* and *surprise* both including Avoidance. For example, *happiness* was never misclassified as *fear* or *surprise*. On another hand, *happiness* was recognized as *anger* in 6% of cases, and both these emotions were designed using an Approach parameter.

6.4.3 Modelling Parameters: Energy

We used high Energy for designing the expressions of *fear*, *surprise* and *anger*, and low Energy for the expressions of *sadness*. In this section, we present a relation between the design parameter of Energy and the three perceived emotional dimensions of valence, arousal and dominance, in order to understand how this design parameter influence the recognition of the designed emotional expressions. The findings explain a small number of misclassifications between the emotions of *fear* or *anger*, both of which represent high Energy, and the emotion of *sadness* representing low Energy.

A repeated measures ANOVA with a Greenhouse-Geisser correction revealed that the mean scores of valence for different energy levels differed statistically significantly ($F(2.73,90.16) = 16.02$, $p < 0.0005$), the same as the mean scores of dominance ($F(2.19,72.58) = 9.94$, $p < 0.0005$) and arousal ($F(2.31,76.25) = 80.45$, $p < 0.0005$). Expressions implemented with a high energy statistically significantly reduced the valence and dominance perception comparing to both a medium energy ($p < 0.0005$), low energy ($p = 0.002$ for valence and $p = 0.038$ for dominance) and a neutral expression ($p < 0.0005$ for valence and $p = 0.022$ for dominance). Therefore, we can conclude that a high energy of expression elicits a statistically significant reduction in the perception of valence and dominance. At the same time, higher speed representing higher energy of expressions significantly raised perceived arousal when changing from low to medium ($p < 0.0005$) and from medium to high level ($p = 0.014$). The mean values of the ratings of valence, arousal and dominance for all the robot emotional expressions of low, medium and high energy are presented in Figure 6-11.

These findings help explain a little number of misclassification between the emotions of *fear* or *anger*, both of which represent high Energy, and the emotion of *sadness* representing low Energy. For example, *fear* was never misclassified as *sadness* and *anger* was misclassified as *sadness* in only 9% of cases. At the same time *anger* was misclassified as *surprise*, designed with the same level of Energy, in 21% of cases.

6.4.4 Modelling Parameters: Intensity

We used high Intensity to design the expressions of *fear*, *happiness*, *surprise* and *anger*, and low Intensity for the expressions of *sadness*. In this section, we present a relation between the design parameter of Intensity and the three perceived emotional dimensions

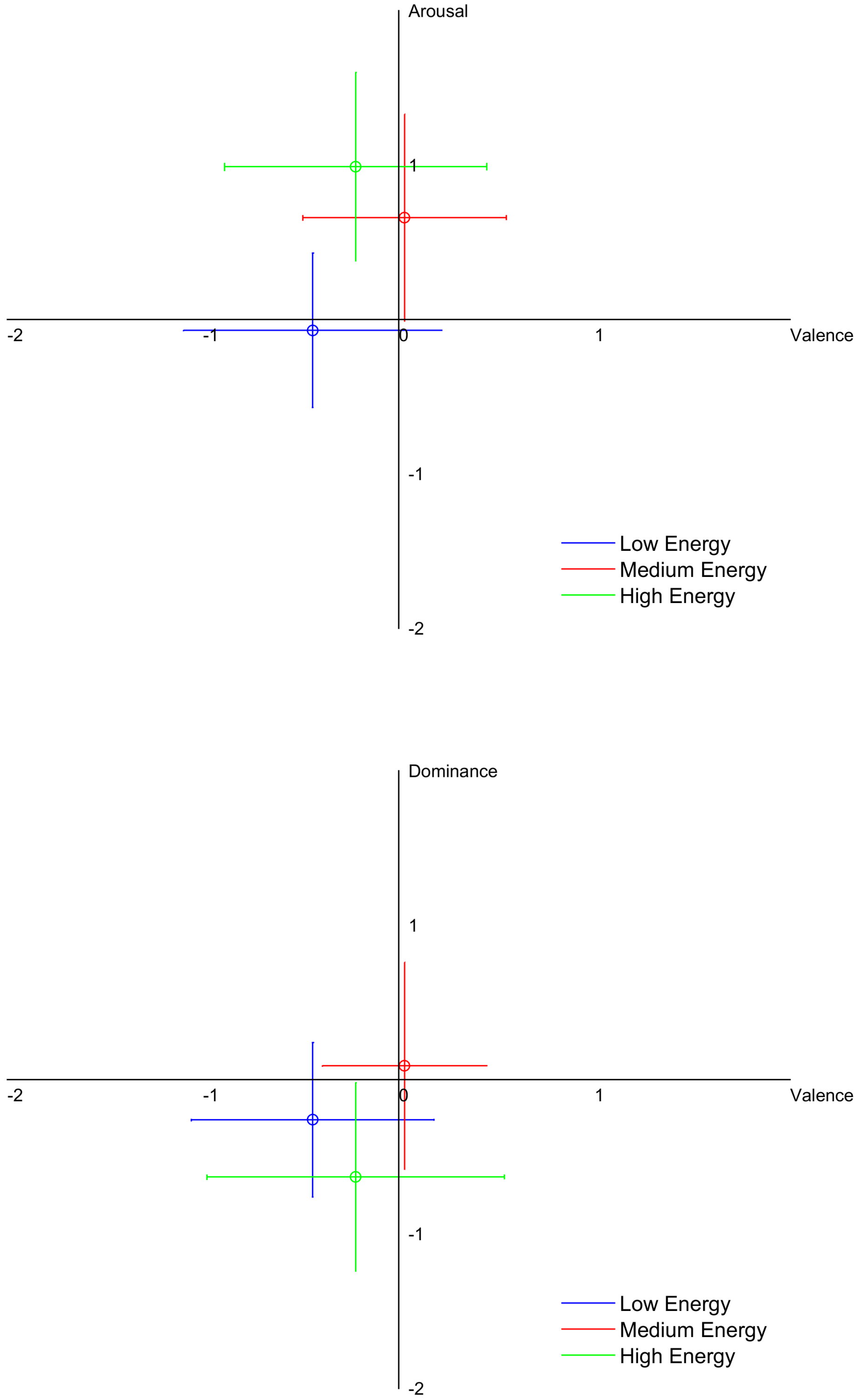


Figure 6-11: *Plots of the Mean values and Standard Deviation of the ratings for the emotional exressions of low, medium and high energy.*

of valence, arousal and dominance, in order to find the relation between this design parameter and the recognition of the designed expressions. The findings presented in this section do not provide enough evidence to claim that the design parameter of Intensity helps in recognizing any specific emotion.

A repeated measures ANOVA test with a Greenhouse-Geisser correction did not find any statistically significant difference of perceived valence ($F(1.00,33.00) = 0.28$, $p = 0.60$) or dominance ($F(1.00,33.00) = 2.07$, $p = 0.16$) between different intensity levels. However, higher intensity determined a significant increase in arousal perception of expression ($F(1.00,33.00) = 154.94$, $p < 0.0005$).

These findings do not provide enough evidence to claim that the design parameter of Intensity helped recognizing any specific emotion. Based on this parameter, the emotional expression of *sadness* was designed exploring low intensity, while all the other emotional expressions of robot were designed using high Intensity of movements. The recognition ratio of *sadness* was as low as 12% and it was misclassified as other emotions regularly.

6.4.5 Modelling Parameters: Duration

We used short Duration to design the expressions of *fear* and *surprise*, medium Duration for the expressions of *happiness* and *anger*, and long Duration for the expressions of *sadness*. In this section, we present a relation between the design parameter of Duration and the three perceived emotional dimensions of valence, arousal and dominance, in order to understand how this design parameter influence the recognition of the designed emotional expressions. The findings show that short and medium Duration of expression influence a significantly different perception of valence and thus help successfully discriminate between *happiness* and *fear*. At the same time, this design parameter helps to separate *fear* from *anger*.

Regarding a duration of robot expressions, a repeated measures ANOVA with a Greenhouse-Geisser correction revealed a statistically significant difference in perception of both valence ($F(2.72,89.74) = 6.4$, $p < 0.005$), arousal ($F(2.54,83.87) = 72.893$, $p < 0.0005$) and dominance ($F(2.23,73.51) = 11.0$,$p < 0.0005$). Valence perceived for the expression with a short duration (up to 1 sec) was significantly lower ($p = 0.003$) than valence of the expressions of a longer duration (2 to 3.3 sec). Low and medium duration of expressions (positive up to 3.3 sec) was perceived with a significantly ($p < 0.0005$) higher arousal level than a long duration of an expression (12 sec), thus making long duration a good indicator of negative arousal.

Medium duration of expression resulted in a significantly ($p < 0.05$) higher perceived dominance level than low or high levels of expression's duration. The mean values of the rating of valence, arousal and dominance for all the robot's emotional expressions of short, medium and long duration are presented in Figure 6-12.

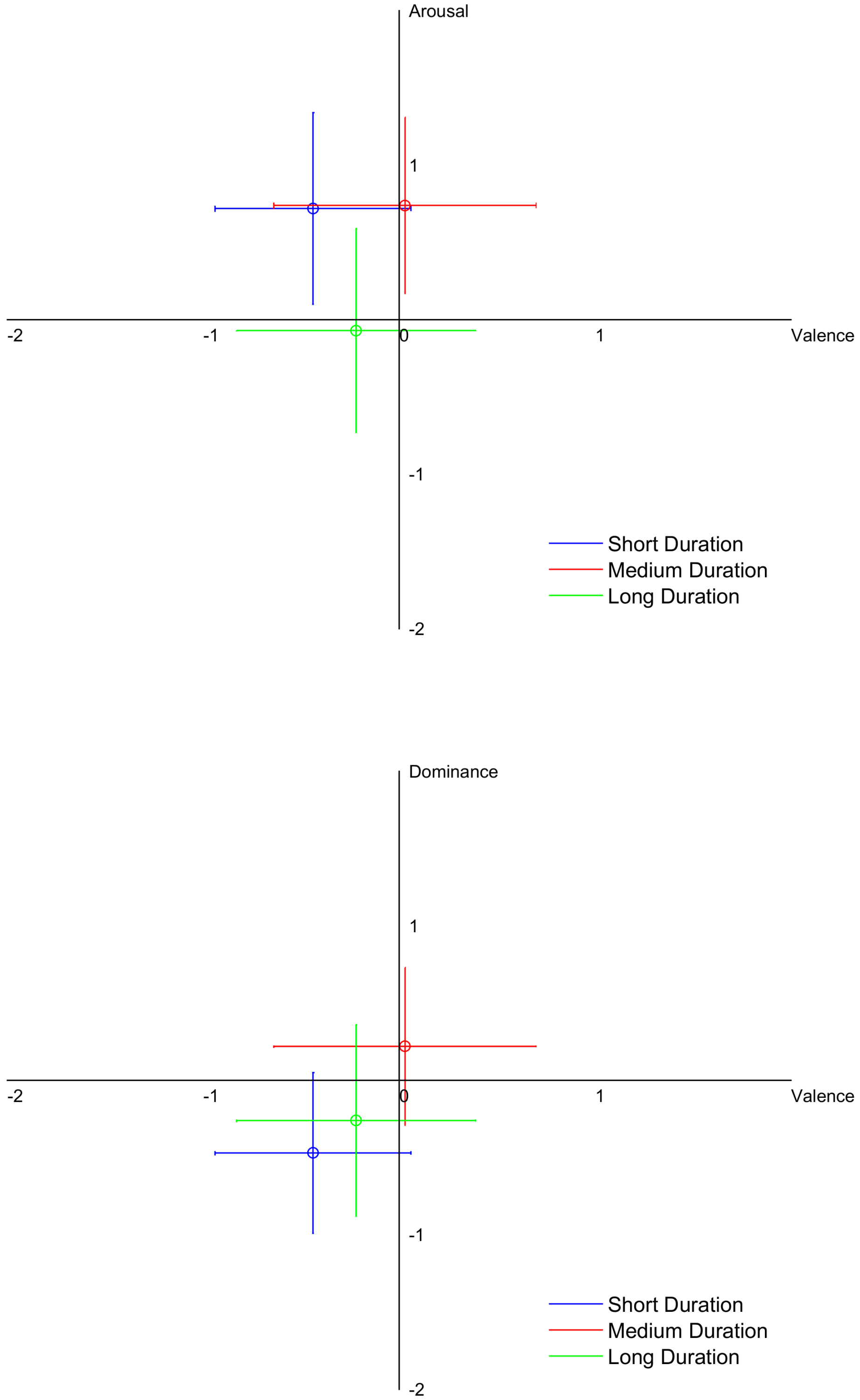


Figure 6-12: *Plots of the Mean values and Standard Deviation of the ratings for the emotional expressions of short, medium and long duration.*

Based on these findings, short and medium Duration of expression influence a significantly different perception of valence and thus help successfully discriminate between such emotions as e.g. *happiness* and *fear*. At the same time, this design parameter helps to separate e.g. *fear* from *anger*, as short Duration indicates significantly lower perceived dominance comparing to medium Duration.

6.4.6 Modelling Parameters: Frequency

We used high Frequency to design the expressions of *fear* and *surprise*, medium Frequency for the expressions of *happiness* and *anger*, and low Frequency for the expressions of *sadness*. In this section, we present a relation between the design parameter of Frequency and the three perceived emotional dimensions of valence, arousal and dominance, in order to understand how this design parameter influence the recognition of the designed emotional expressions. The parameter of Frequency is applicable to signal different levels of arousal whose perceived level raises together with the level of Frequency. It is also good for emphasizing dominance. Low Frequency results in negative dominance, while medium Frequency indicates positive dominance. The findings presented in this section explain the small number of misclassifications between the emotions of *fear* and *anger*.

A repeated measures ANOVA with a Greenhouse-Geisser correction revealed a statistically significant difference in perception of both valence ($F(2.73,90.16) = 16.02$, $p < 0.005$), arousal ($F(2.31,76.25) = 80.45$, $p < 0.0005$) and dominance ($F(2.20,72.58) = 9.94$, $p < 0.0005$) for different frequency levels.

Valence perceived for the expression with a high frequency (1.6 movement/sec) was significantly lower ($p < 0.005$) than any other level of frequency (0-1 movement/sec). Any increase in frequency rate significantly increases ($p < 0.05$) a perception of expression's arousal. Both low and high frequency of emotional expressions corresponds to a negative dominance, which is significantly different ($p < 0.05$) from a positive perceived dominance of an expression of a medium frequency. The mean values of the rating of valence, arousal and dominance for all the robot's emotional expressions of low, medium and high frequency are presented in Figure 6-13.

The parameter of Frequency is not only applicable to signal different levels of arousal which perceived level raises together with the level of Frequency, but it is also good for emphasizing dominance. Low Frequency results in negative dominance, while medium Frequency indicates positive dominance. These findings help explain the small number of misclassification between the emotions of *fear* and *anger* in our study. The expression of *anger* was recognized as *fear* in only 4% of cases, while *fear* was never recognized as *anger* at all.

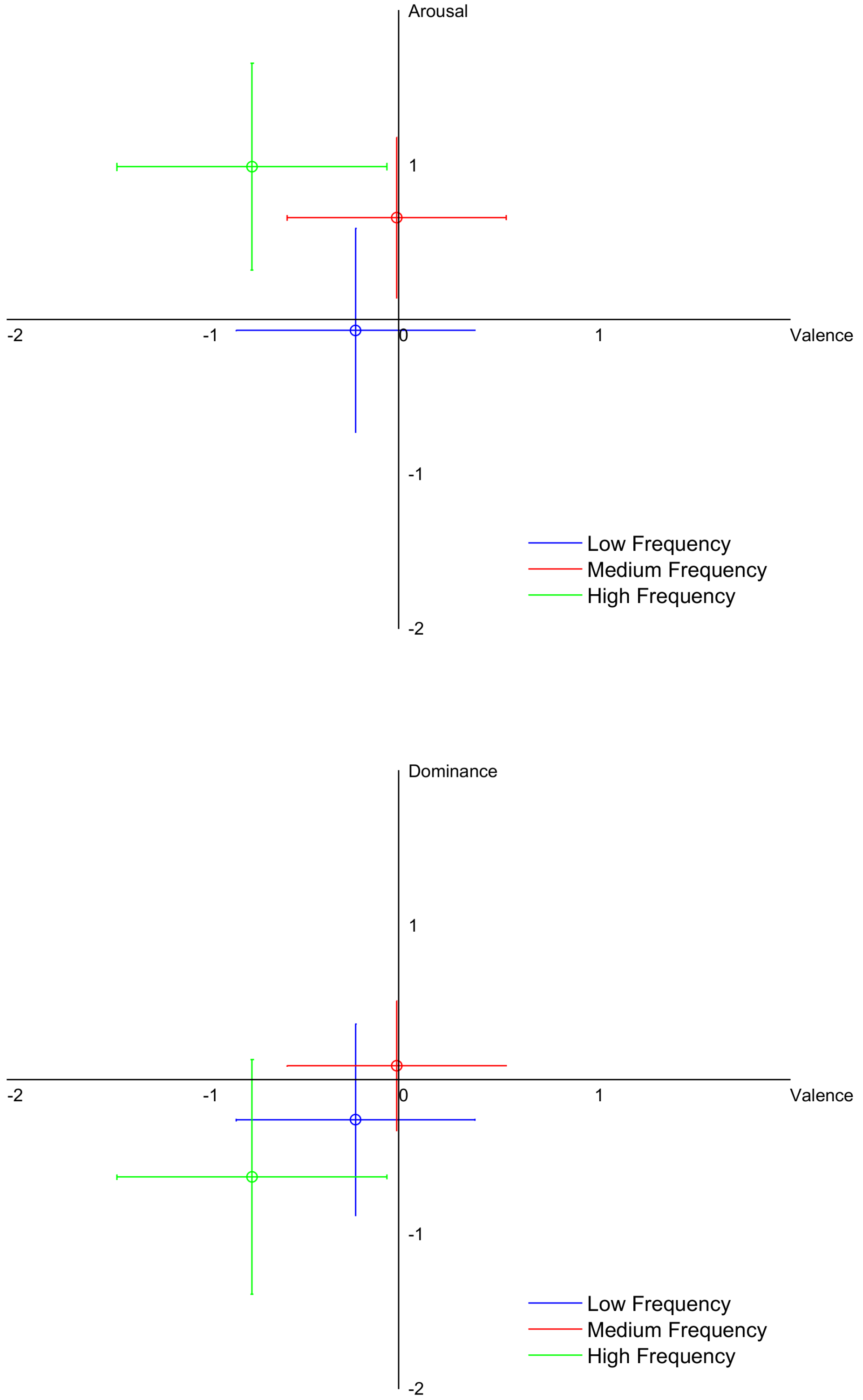


Figure 6-13: *Plots of the Mean values and Standard Deviation of the ratings for the emotional expressions of low, medium and high frequency.*

6.4.7 Attitudes Towards the Robot

We used a paired samples t-test to investigate whether emotional robot behaviour impacts the attitudes of a human observers towards the robot. We compared two conditions: 1) the condition, where the robot was performing emotional expressions of fear, anger, happiness, sadness and surprise within an appropriate context, 2) the condition, where the robot was not performing any emotional expression within the same context. The observers' attitudes were rated on a 5-point Likert scales, with the minimal value of 1 and the maximum value of 5.

The results reported in this section demonstrate that people perceive emotionally expressive robots as more anthropomorphic, more animate and even more likeable. Specifically, in terms of Anthropomorphism, emotional robots expressing any of five basic emotions of fear, anger, happiness, sadness or surprise were perceived as being more natural, more humanlike and more conscious. The same was the case with perceived Animacy of the robots expressing these five emotions, when emotional robots were rated as more organic, lifelike and responsive comparing to non-emotional. In terms of Likeability, emotional robots expressing fear, happiness, sadness or surprise were perceived as more pleasant and being liked more than non-emotional.

Perceived Anthropomorphism

In this section, in order to asses the effect of robotic emotional body expressions on people's attitude towards the robot, we show the difference in perceived Anthropomorphism between the emotionally expressive robot and the non-emotional robot.

The statistical results of the mean and standard deviation values of perceived Anthropomorphism of the E4 robot in two conditions are presented in the Table 6.9 and graphically in the Figure 6-14.

The Anthropomorphism was evaluated using three scales: 1) Fake / Natural, 2) Machinelike / Humanlike, and 3) Unconscious / Conscious. Higher values mean that the observers were rating the robot as more natural, humanlike and conscious. Lower values mean that the robot was rated as more fake, machinelike and unconscious.

The robot performing an emotional expression of *fear* was rated as the most natural (Mean = 3.97, SD = 0.93), while the robot performing the expression of *surprise* was evaluated as the least natural (Mean = 3.38, SD = 1.18) amongst the emotionally expressive robots. However, when the robot was not expressing emotions, its highest average rate on the Fake / Natural scale was 2.58 only (SD = 1.20), which is much lower than the lowest value for the emotionally expressive robot. The lowest value on this scale for not emotional robot behaviours was as low as 1.94 (SD = 1.05).

The robot performing an emotional expression of *happiness* was rated as the most humanlike (Mean = 3.73, SD = 1.13), while the robot performing the expression of *anger* was evaluated as the least humanlike (Mean = 3.09, SD = 1.03) amongst the

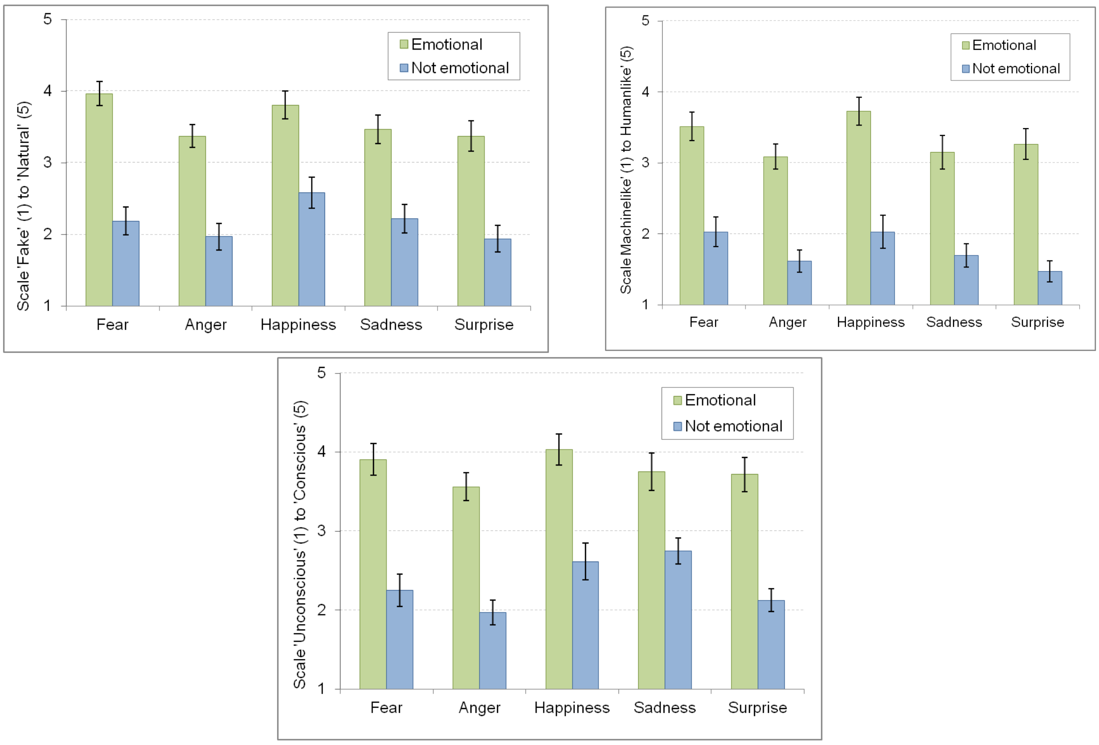


Figure 6-14: *Plot of mean and standard deviation values of perceived Anthropomorphism of emotional and note emotional behaviours of the E4 robot on the scales Fake/Natural, Machine-/Humanlike and Un-/Conscious.*

emotionally expressive robots. However, when the robot was not expressing emotions, its highest average rate on the Machinelike / Humanlike scale was 2.03 only (SD = 1.33), which is much lower than the lowest value for the emotionally expressive robot. The lowest value on this scale for not emotional robot behaviours was as low as 1.47 (SD = 0.86), which means that the robot was perceived as almost completely machinelike.

The robot performing an emotional expression of *happiness* was rated as the most conscious (Mean = 4.03, SD = 0.95), while the robot performing the expression of *anger* was evaluated as the least conscious (Mean = 3.56, SD = 1.01) amongst the emotionally expressive robots. However, when the robot was not expressing emotions, its highest average rate on the Unconscious / Conscious scale was 2.75 (SD = 1.55), which is much lower than the lowest value for the emotionally expressive robot. The lowest value on this scale for not emotional robot behaviours was as low as 1.97 (SD = 1.20).

In general, the emotionally expressive robot was rated significantly higher when evaluating perceived Anthropomorphism, than the non-emotional robot. The summary of the t-test results for each emotional expression are presented in the Table 6.10, in the Anthropomorphism section. As the Table shows, the t-test revealed a significant difference with $p < 0.0005$ in the observers' ratings for all the five emotional expressions

		Fake / Natural		Machine- / Humanlike		Un- / Conscious	
		Mean	StDev.	Mean	StDev.	Mean	StDev.
fear	emotional	3.97	0.93	3.52	1.15	3.91	0.89
	not emotional	2.19	1.12	2.03	1.19	2.25	1.34
anger	emotional	3.38	0.91	3.09	1.03	3.56	1.01
	not emotional	1.97	1.06	1.62	0.92	1.97	1.20
happiness	emotional	3.81	1.08	3.73	1.13	4.03	0.95
	not emotional	2.58	1.20	2.03	1.33	2.61	1.41
sadness	emotional	3.47	1.11	3.15	1.35	3.75	1.14
	not emotional	2.22	1.13	1.70	0.95	2.75	1.55
surprise	emotional	3.38	1.18	3.26	1.26	3.72	1.20
	not emotional	1.94	1.05	1.47	0.86	2.13	1.26

Table 6.9: *Mean and standard deviation values of perceived Anthropomorphism of emotional and note emotional behaviours of the E4 robot.*

on the scales Fake / Natural and Machine- / Humanlike. On the scale Unconscious / Conscious, the t-test revealed a significant difference with $p < 0.0005$ for the emotional expressions of *fear, anger, happiness* and *surprise*, and the significant difference on the level $p < 0.05$ for the emotional expression of *anger*.

Perceived Animacy

In this section, in order to asses the effect of robotic emotional body expressions on people's attitude towards the robot, we show the difference in perceived Animacy between the emotionally expressive robot and the non-emotional robot.

The statistical results of the mean and standard deviation values of perceived Animacy of the E4 robot in two conditions are presented in the Table 6.11 and graphically in the Figure 6-15.

The Animacy was evaluated using three scales: 1) Mechanical / Organic, 2) Artificial / Lifelike, and 3) Apathetic / Responsive. Higher values mean that the observers were rating the robot as more organic, lifelike and responsive. Lower values mean that the robot was rated as more mechanical, artificial and apathetic.

The robot performing an emotional expression of *fear* was rated as the most organic (Mean = 3.16, SD = 1.08), while the robot performing the expression of *anger* was evaluated as the least organic (Mean = 2.65, SD = 1.04) amongst the emotionally expressive robots. However, when the robot was not expressing emotions, its ratings on the Mechanical / Organic scale ranged between 1.59 and 1.97. The lowest value on this scale for not emotional robot behaviours was as low as 1.59(SD = 0.92), which means that the robot was perceived as almost completely mechanical.

The robot performing an emotional expression of *fear* was rated as the most lifelike (Mean = 3.78, SD = 0.97), while the robot performing the expression of *anger* was evaluated as the least lifelike (Mean = 2.75, SD = 1.05) amongst the emotionally

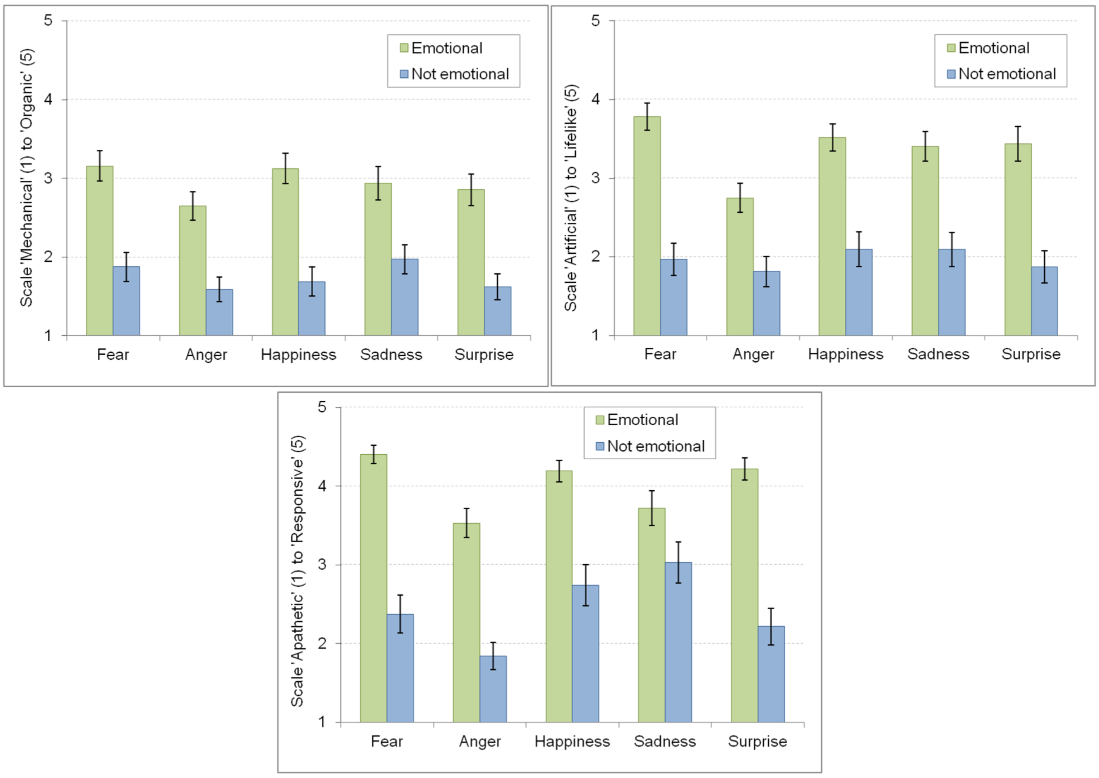


Figure 6-15: *Plot of mean and standard deviation values of perceived Animacy of emotional and note emotional behaviours of the E4 robot on the scales Mechanical/Organic, Artificial/Lifelike and Apathetic/Responsive.*

expressive robots. However, when the robot was not expressing emotions, its highest average rate on the Artificial / Lifelike scale was 2.10 only (SD = 1.22), which is lower than the lowest value for the emotionally expressive robot. The lowest value on this scale for not emotional robot behaviours was as low as 1.81 (SD = 1.09).

The robot performing an emotional expression of *fear* was rated as the most responsive (Mean = 4.41, SD = 0.67), while the robot performing the expression of *anger* was evaluated as the least responsive (Mean = 3.53, SD = 1.05) amongst the emotionally expressive robots. However, when the robot was not expressing emotions, its highest average rate on the Apathetic / Responsive scale was 3.03 (SD = 1.49), which is lower than the lowest value for the emotionally expressive robot. The lowest value on this scale for not emotional robot behaviours was as low as 1.84 (SD = 0.99).

In general, the emotionally expressive robot was rated significantly higher when evaluating perceived Animacy than the non-emotional robot, as presented in the Table 6.10, in the Animacy section. As the Table shows, the t-test revealed a significant difference with $p < 0.0005$ in the observers' ratings on all three scales for the emotional expressions of *fear, happiness* and *surprise*. The t-test revealed a significant difference between emotional and not emotional robots with $p < 0.0005$ in the observers' ratings on the scale Mechanical/Organic for the expression of *anger*. On the two other Ani-

		fear	anger	happiness	sadness	surprise
Anthropomorphism	Fake / Natural	$t(31) = 6.46$, $p < 0.0005$	$t(31) = 5.83$, $p < 0.0005$	$t(30) = 3.91$, $p < 0.0005$	$t(31) = 4.85$, $p < 0.0005$	$t(31) = 5.76$, $p < 0.0005$
	Machine- / Humanlike	$t(32) = 4.73$, $p < 0.0005$	$t(33) = 5.77$, $p < 0.0005$	$t(32) = 4.97$, $p < 0.0005$	$t(32) = 5.49$, $p < 0.0005$	$t(33) = 7.31$, $p < 0.0005$
	Un- / Conscious	$t(31) = 4.90$, $p < 0.0005$	$t(31) = 5.55$, $p < 0.0005$	$t(30) = 4.30$, $p < 0.0005$	$t(31) = 2.66$, $p < 0.05$	$t(31) = 4.75$, $p < 0.0005$
Animacy	Mechanical / Organic	$t(31) = 4.74$, $p < 0.0005$	$t(33) = 4.07$, $p < 0.0005$	$t(31) = 4.94$, $p < 0.0005$	$t(32) = 3.55$, $p = 0.001$	$t(33) = 5.34$, $p < 0.0005$
	Artificial / Lifelike	$t(31) = 7.09$, $p < 0.0005$	$t(31) = 3.70$, $p < 0.005$	$t(30) = 4.57$, $p < 0.0005$	$t(31) = 4.44$, $p = 0.0005$	$t(31) = 5.25$, $p < 0.0005$
	Apathetic / Responsive	$t(31) = 8.19$, $p < 0.0005$	$t(31) = 6.23$, $p < 0.005$	$t(30) = 4.53$, $p < 0.0005$	**$t(31) = 1.81$, $p = 0.08$**	$t(31) = 7.23$, $p < 0.0005$
Likeability	Dislike / Like	$t(31) = 3.19$, $p < 0.005$	**$t(31) = 1.22$, $p = 0.23$**	$t(30) = 3.82$, $p < 0.005$	$t(31) = 2.27$, $p < 0.05$	$t(31) = 3.19$, $p < 0.005$
	Un- / Pleasant	$t(31) = 2.56$, $p < 0.05$	**$t(31) = -0.17$, $p = 0.87$**	$t(30) = 4.07$, $p < 0.0005$	$t(31) = 3.79$, $p < 0.005$	$t(31) = 2.25$, $p < 0.05$
Intelligence	Irr- / Responsible	**$t(31) = 0.96$, $p = 0.34$**	$t(31) = 2.25$, $p < 0.05$	**$t(31) = 1.71$, $p = 0.09$**	**$t(31) = 0.66$, $p = 0.52$**	$t(32) = 2.41$, $p < 0.05$
	Un- / Intelligent	$t(31) = 4.79$, $p < 0.0005$	$t(33) = 3.41$, $p < 0.005$	$t(30) = 2.56$, $p < 0.05$	$t(31) = 2.62$, $p < 0.05$	$t(31) = 3.67$, $p < 0.005$
	Foolish / Sensible	**$t(31) = 0.96$, $p = 0.34$**	$t(31) = 2.25$, $p < 0.05$	**$t(31) = 1.71$, $p = 0.09$**	**$t(31) = 0.66$, $p = 0.52$**	$t(31) = 2.41$, $p < 0.05$

Table 6.10: *The results of a paired samples t-test for each presented robot emotional expression. The non-significant results are marked in bold.*

		Mechanical / Organic		Artificial / Lifelike		Apathetic / Responsive	
		Mean	StDev.	Mean	StDev.	Mean	StDev.
fear	emotional	3.16	1.08	3.78	0.97	4.41	0.67
	not emotional	1.88	1.04	1.97	1.15	2.38	1.36
anger	emotional	2.65	1.04	2.75	1.05	3.53	1.05
	not emotional	1.59	0.92	1.81	1.09	1.84	0.99
happiness	emotional	3.13	1.10	3.52	0.96	4.19	0.75
	not emotional	1.69	1.06	2.10	1.22	2.74	1.46
sadness	emotional	2.94	1.22	3.41	1.07	3.72	1.25
	not emotional	1.97	1.07	2.09	1.23	3.03	1.49
surprise	emotional	2.85	1.16	3.44	1.24	4.22	0.79
	not emotional	1.62	0.95	1.88	1.16	2.22	1.31

Table 6.11: *Mean and standard deviation values of perceived Animacy of emotional and note emotional behaviours of the E4 robot.*

macy scales the emotional robot expressing *anger* was rated significantly higher than not emotional, with $p < 0.005$. The emotional robot expressing *sadness* was rated significantly higher than not emotional on the scales Mechanical/Organic and Artificial/Lifelike, with $p < 0.005$. However, the emotional robot expressing *sadness* was not rated significantly differently from a not emotional on the scale Apathetic/Responsive.

Likeability

In this section, in order to asses the effect of robotic emotional body expressions on people's attitude towards the robot, we show the difference in Likeability between the emotionally expressive robot and the non-emotional robot.

The statistical results of the mean and standard deviation values of Likeability for the E4 robot in two conditions are presented in the Table 6.12 and graphically in the

Figure 6-16.

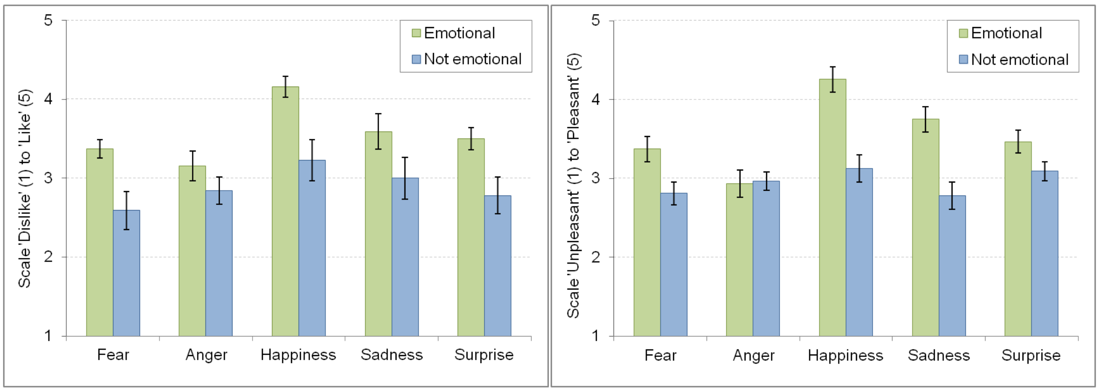


Figure 6-16: *Plot of mean and standard deviation values of detected Likeability of emotional and note emotional behaviours of the E4 robot on the scales Dislike/Like and Un-/Pleasant.*

The Likeability was evaluated using two scales: 1) Dislike / Like, and 2) Unpleasant / Pleasant. Higher values mean that the observers were rating the robot as more pleasant and demonstrated they liked it more. Lower values mean that the robot was rated as more unpleasant and was disliked more.

The robot performing an emotional expression of *happiness* was rated as the most liked (Mean = 4.16, SD = 0.90), while the robot performing the expression of *anger* was evaluated as the least liked (Mean = 3.16, SD = 1.08) amongst the emotionally expressive robots. However, when the robot was not expressing emotions, its highest average rate on the Dislike / Like scale was 3.23 (SD = 0.76). The lowest value on this scale for not emotional robot behaviours was as low as 2.59 (SD = 0.91).

The robot performing an emotional expression of *happiness* was rated as the most pleasant (Mean = 4.26, SD = 0.89), while the robot performing the expression of *anger* was evaluated as the least pleasant (Mean = 2.94, SD = 0.98) amongst the emotionally expressive robots. However, when the robot was not expressing emotions, its highest average rate on the Unpleasant / Pleasant scale was 3.13 (SD = 0.96). The lowest value on this scale for not emotional robot behaviours was as low as 2.78 (SD = 0.97).

In general, the emotionally expressive robot was rated significantly higher when evaluating Likeability than the non-emotional robot, as presented in the Table 6.10, in the Likeability section. As the Table shows, the t-test revealed a significant difference in the observers' ratings on all three scales for the emotional expressions of *fear, happiness, sadness* and *surprise*. However, the emotional robot expressing *anger* was not rated significantly differently from a not emotional one on any of Likeability scales.

Perceived Intelligence

In this section, in order to asses the effect of robotic emotional body expressions on people's attitude towards the robot, we show the difference in perceived Intelligence

		Dislike / Like		Un- / Pleasant	
		Mean	StDev.	Mean	StDev.
fear	emotional	3.38	0.98	3.38	0.91
	not emotional	2.59	0.91	2.81	0.82
anger	emotional	3.16	1.08	2.94	0.98
	not emotional	2.84	0.77	2.97	0.65
happiness	emotional	4.16	0.90	4.26	0.89
	not emotional	3.23	0.76	3.13	0.96
sadness	emotional	3.59	1.10	3.75	0.92
	not emotional	3.00	1.02	2.78	0.97
surprise	emotional	3.50	0.92	3.47	0.80
	not emotional	2.78	1.01	3.09	0.69

Table 6.12: *Mean and standard deviation values of detected Likeability for emotional and note emotional behaviours of the E4 robot.*

		Ir- / Responsible		Un- / Intelligent		Foolish / Sensible	
		Mean	StDev.	Mean	StDev.	Mean	StDev.
fear	emotional	3.28	0.92	3.63	0.83	3.34	0.97
	not emotional	3.06	1.08	2.44	1.13	3.16	0.92
anger	emotional	2.72	1.11	2.88	0.95	2.38	1.07
	not emotional	2.16	1.05	2.03	0.97	2.28	1.05
happiness	emotional	3.97	0.82	3.90	0.79	3.72	0.96
	not emotional	3.59	1.01	3.26	1.12	3.41	0.76
sadness	emotional	3.47	0.95	3.56	0.91	3.53	0.95
	not emotional	3.28	1.28	2.84	1.17	3.16	1.22
surprise	emotional	3.55	0.83	3.47	0.88	3.41	0.87
	not emotional	2.97	1.05	2.50	1.19	3.13	0.83

Table 6.13: *Mean and standard deviation values of perceived Intelligence of emotional and note emotional behaviours of the E4 robot.*

between the emotionally expressive robot and the non-emotional robot.

The statistical results of the mean and standard deviation values of perceived Intelligence for the E4 robot in two conditions are presented in the Table 6.13 and graphically in the Figure 6-17.

The perceived Intelligence was evaluated using three scales: 1) Irresponsible / Responsible, 2) Unintelligent / Intelligent, and 3) Foolish / Sensible. Higher values mean that the observers were rating the robot as more responsible, intelligent and sensible. Lower values mean that the robot was rated as more irresponsible, unintelligent and foolish.

The robot performing an emotional expression of *happiness* was rated as the most responsible (Mean = 3.97, SD = 0.82), while the robot performing the expression of *anger* was evaluated as the least responsible (Mean = 2.72, SD = 1.11) amongst the emotionally expressive robots. When the robot was not expressing emotions, its highest

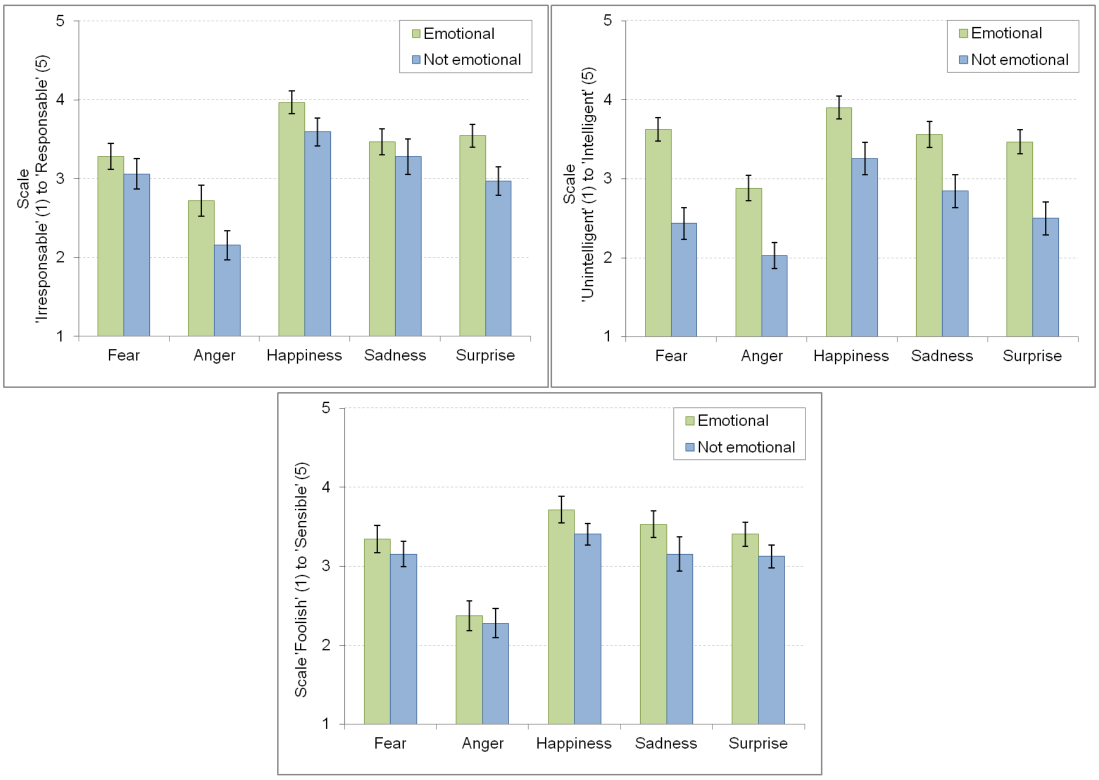


Figure 6-17: *Plot of mean and standard deviation values of perceived Intelligence of emotional and note emotional behaviours of the E4 robot on the scales Ir-/Responsible, Un-/Intelligent and Foolish/Sensible.*

average rate on the Irresponsible / Responsible scale was 3.59 (SD = 1.01). The lowest value on this scale for not emotional robot behaviours was as low as 2.16 (SD = 1.05).

The robot performing an emotional expression of *happiness* was rated as the most intelligent (Mean = 3.90, SD = 0.79), while the robot performing the expression of *anger* was evaluated as the least intelligent (Mean = 2.88, SD = 0.95) amongst the emotionally expressive robots. When the robot was not expressing emotions, its highest average rate on the Unintelligent / Intelligent scale was 3.26 (SD = 1.12). The lowest value on this scale for not emotional robot behaviours was as low as 2.03 (SD = 0.97).

The robot performing an emotional expression of *happiness* was rated as the most sensible (Mean = 3.72, SD = 0.96), while the robot performing the expression of *anger* was evaluated as the least sensible (Mean = 2.38, SD = 1.07) amongst the emotionally expressive robots. When the robot was not expressing emotions, its highest average rate on the Unintelligent / Intelligent scale was 3.41 (SD = 0.76). The lowest value on this scale for not emotional robot behaviours was as low as 2.28 (SD = 1.05).

The situation with perceived Intelligence of the emotional and not emotional robot is quite different from other perceived attitudes towards the robot. In many cases, the emotional robot was not rated in a significantly different way than the non-emotional, e.g. there was no statistically significant difference between the emotional robot expressing *fear, happiness* or *sadness* and the non-emotional robot on the scales Irresponsible/Responsible and Foolish/Sensible. However, the t-test revealed a significant difference in the observers' ratings on the scale Unintelligent/Intelligent for all the five emotional expressions of the robot.

6.5 Discussion

We proposed a design scheme for expressing and interpreting emotional movements in non-humanoid robots that is based on a behavioural form of approach-avoidance analysed from an observer's point of view and the Labanian theory of movement analysis. We implemented the expressions of five basic emotions into a non-humanoid Lego robot. Let us examine how the study answered our research questions.

a) Do expressions designed according to the framework help people to understand five basic emotions implemented in a non-humanoid robot with a better than chance recognition level?

The results of the performed study showed that the values of recognition ratio exceeded the chance level for four recognized emotions: fear, anger, happiness and surprise. The recognition ratio for the emotion of sadness was lower than a chance level, so we can conclude that this specific emotional expression was not recognized correctly by the subjects. The reasons could be explained by comparing the current results with the results of several previous studies.

Table 6.14 compares the results of a recognition ratio within an appropriate context with the results of the similar previous experiments, where a) the same robot expressed emotions in a dynamic way without a context, as discussed through the second study in Chapter 4, b) the same robot expressed emotions in a static way without a context, as discussed through the first study in Chapter 4, c) 70-cm tall Lego robot Feelix expressed emotions using facial features [36], d) 23 DoF robot EDDIE expressed emotions using facial features and some animal-inspired attributes [169].

The recognition ratio for anger, happiness and surprise in our study were higher comparing to all previous experiments, as presented in the Table 6.14. The recognition ratio of fear in our study was higher than that of the studies with Feelix, Eddie and static pictures of the same robot, although lower than our previous study with dynamic robot expressions. The only difference in the current expression of fear with the previous study is the existence of a context. Thus we could suggest that either a context for this expression was not chosen correctly, or the expression of fear is better recognized without any specific context. More experiments should be performed with this robotic expression in different contexts and without it in order to prove any of these hypotheses.

The recognition ratio of sadness was extremely low in our current study and has not even reached the chance level. However, a comparison with previous experiments

Expressed emotion	Current study, appropriate context	Same robot, dynamic expressions, no context	Same robot, static images	Feelix	Eddie
afraid	56%	68%	42%	16%	42%
angry	52%	36%	15%	40%	54%
happy	94%	32%	36%	60%	58%
surprised	85%	57%	52%	37%	75%
sad	12%	14%	41%	70%	58%

Table 6.14: *Comparison of our results with the results of the similar previous experiments.*

suggests that the emotion of sadness is much better recognized from facial cues, as with Eddie and Feelix robots. On the other hand, a static picture of the expression of sadness is recognized with a significantly higher ratio than a dynamic expression. Earlier in this chapter we have mentioned that some emotions are easier conveyed using a body than using a face [5]. Our results suggest that the emotion of sadness is the one which is expressed more powerfully using static facial feature and not the dynamic body language. If we focus on the specific features of the expression of sadness, we can notice that it is often described as slow, long movements of a low frequency, when limbs and head are kept close to the body, not moving. All this shows the intention to be as non-dynamic as possible during the expression of sadness. That's why, probably, the static picture represents sadness much better than any dynamic expression. However, more experiments need to be performed in order to support this hypothesis.

In general, the results show that for such an emotional state as sadness a static facial expression fits more than dynamic bodily emotional expressions. Other emotions, especially surprise and happiness, can be expressed in robots using a body language at least as successfully as facial features, and often even more successfully.

b) What is the relation between our framework's parameters and the recognized dimensions of valence, arousal and dominance?

The results of the study support our basic claim: the parameters of the design framework can be used as a model for implementation in a non-humanoid robot so that they can be related to perceived levels of valence, arousal and dominance. The design framework is conceptual tool that combines three dimensions of approach-avoidance, Shape and Effort. The model defines an architectural relationship between these ideas, bridging the framework and the implementation.

Arousal, according to the result of the study, was increased by both approach and avoidance behaviours, high intensity or an increase of speed of an expression, as well as an increase of frequency of limbs' movements. Decreased arousal, on the other hand, was related to a short or medium duration of an expression, low intensity and a context of a negative arousal.

The results show that it is easier to decrease a perceived valence of an expression by making it of a short duration or high speed, by increasing the frequency of limb movements to a high level, or by expressing avoidance. All the parameters mentioned make valence negative. In order to increase a perceived valence, an expression needs to be tied to a context of positive valence. An expression of approach increases a perceived valence and makes it positive.

Changing a perception of dominance by controlling parameters of our design model is similar to changing the perception of valence. As with valence, high speed of expression, high frequency of limb movements and avoidance all decrease the level of perceived dominance and make it negative (i.e. subjugated). Also as with valence, a context of positive valence tied to an expression increases the level of perceived dominance. However, the situation is different with a parameter of a duration of an expression: a medium duration of an expression increases the level of dominance and makes it positive, contrasting with duration's influence on valence.

In general, these results conform to a certain degree to what was shown by previous research that linked e.g. strong, jerk and intensive approaching movements to anger [44, 85, 41, 180], or linked a short and fast movements together with an avoidance behaviour to fear [74, 41]. Such a correspondence is suggested by making one more step and associating e.g. anger with a negative valence, high arousal and high dominance, while fear can be associated with a negative valence, high arousal and low dominance. However, such a link is not straightforward and is sometimes arguable. Our results however expand previous work by showing a direct link between the parameters of our suggested design framework and all three emotional dimensions. Such a broader and more detailed model can help the researchers in implementing a broad range of emotions into non-humanoid robots.

Finally, the results of the study reported in this chapter demonstrate that people perceive emotionally expressive robots as more anthropomorphic, more animate and even more likeable. Specifically, in terms of anthropomorphism, emotional robots expressing any of five basic emotions of *fear, anger, happiness, sadness* or *surprise* were perceived as being more natural, more humanlike and more conscious. The same was the case with perceived animacy of the robots expressing these five emotions, when emotional robots were rated as more organic, lifelike and responsive comparing to non-emotional. In terms of likeability, emotional robots expressing *fear, happiness, sadness* or *surprise* were perceived as more pleasant and being liked more than non-emotional. In addition, the results of the study reported in Chapter 6 revealed that robots were perceived as more responsible when they expressed the emotions of *anger* or *surprise*.

Interestingly, emotional robots expressing any of five basic emotions of *fear, anger, happiness, sadness* or *surprise* were perceived as being more intelligent.

The results of this research suggest that, in a context of a joint human-robot activity, emotionally expressive robots will be able to better engage people in interaction. The enhanced attitude towards emotionally expressive robots could create a higher level of empathy between people and robots and thus improve social coordination between them for the purpose of a better collaboration. Moreover, the results provide the evidence to think that in the context of human-robot teamwork an emotionally expressive robot would be a more preferred team member, trusted more by its human collaborator. Obviously, the functional behaviour of a robot should not contradict this assumption, otherwise the process of a human-robot collaboration would not be efficient.

6.5.1 Limitations

Not all the parameters of Shape and Quality were explored in this study. The robotic platform made it difficult to experiment with some parameters, for example, *Changes in tempo* associated with *anger* or *Indirect trajectory of the movement* associated with *happiness*. These could be seen as redundant with regards to affective interpretations. However, we see these features as important because they reflect a richer palette of opportunities for designers to work with. Robot platforms and form factors vary hugely in the degree of expressiveness that they offer to designers. Consequently, our design scheme should attempt maximize the range of body movements which could represent any given emotional state.

6.6 Conclusion

This chapter has presented research concerning the capacity for creating behavioural expressions of artificial emotions in human-robot interaction. As in human-human non-verbal social communication, expressive movements of the body play an important role in HRI. The goal of this study was to present and validate a general design scheme for expressing artificial emotional states in non-humanoid robots. We proposed a design scheme for modelling emotionally expressive robotic movements.

We posed two main research questions: Do expressions designed according to the proposed framework help people to understand five basic emotions implemented in a non-humanoid robot? What is the relation between our framework's parameters and the emotional dimensions recognized by human observers? We investigated these questions using an exploratory study, where participants observed different expressions implemented in a non-humanoid robot according to the proposed design framework.

The results from this study demonstrate that the emotions of fear, anger, happiness and surprise are recognized on a better-than-chance level when implemented according to our proposed framework and expressed by a non-humanoid robot within an appropriate context. The results suggest that the emotion of sadness is more powerfully expressed using static facial features, not by dynamic body language. In addition, our results show that the parameters of our suggested model are related to the perceived level of valence, arousal and dominance. Thus, our model can be used by HRI researchers as a basis for implementing a set of emotions in non-humanoid robots.

It is important to consider the context of joint human-robot activity when deciding how to map from the VAD dimensional space into the behavioural space. The activity context will condition a person's ability to infer the meaning of a robot's behaviour: it cannot be understood in isolation from the task it is performing, or the human-robot joint activity in which it is engaged. In the next Chapter we will focus on and investigate in more details the effect of environmental context on interpreting robot body movements from the human observer's point of view.

CHAPTER 7

EFFECT OF CONTEXT ON INTERPRETING EMOTIONAL ROBOT BODY MOVEMENTS

7.1 Introduction

In the previous chapter, we presented research concerning the capacity for creating behavioural expressions of artificial emotions in robots using expressive movements of the body. We demonstrated through the results of the study that the emotions of fear, anger, happiness and surprise were recognized on a better-than-chance level when implemented according to the proposed design scheme and expressed by a non-humanoid robot within an appropriate context. However, in real-world HRI scenarios, situational context could be ambiguous and difficult to interpret. For our purposes, situational context is treated as the robot's environment that has the potential to facilitate or inhibit its ability to carry out its work. This conceptualism of context is consistent with our focus on the immediate time frame of a robot's actions and corresponding expressive behaviours. Thus, it is important to understand the impact of the context on the interpretation of robot's expressive behaviour.

This chapter presents a further analysis of the study reported in Chapter 6 and focuses on the interaction between situational context and emotional body language in robots. The effect of such a contextual information on interpreting emotional robot body movements is presented in comparison to the effect of the emotional signals. Context is presented in this chapter as one of the factors influencing people's interpretation of robot expressions, and in such a way this chapter addresses the third research question of this thesis formulated as follows: "RQ3: What factors impact how people interpret the emotionally charged bodily expressions of a robot?"

There exist very few studies analysing the role of situational context in the interpretation of robot emotions and in the area of human-robot emotional interaction in general. One of them is a pilot study conducted and reported by [14], which revealed that the context of a human-robot interaction had a significant impact on the interpretation of robot's body postures. Another recent study was conducted by [141]. Their paper presented an experimental investigation of the influence a situational context had on people's affective interpretation of Non-Linguistic Utterances performed by a social robot. Participants judged the emotional valence of the robot's state when it was being slapped compared to when it was being kissed. Despite the fact that the robot's utterances were always identical, the valence of judgement were consistently lower for "slap" than "kiss" conditions. The results indicate that the interpretation of affective context overrides that of an affective utterance.

The findings of the study presented in this chapter support our hypothesis that an emotional expression overrides the interpretation of a situational context in signalling emotional information. More specifically, they reveal that the perception of arousal for the expressions of *anger, happiness, sadness* and *surprise* is biased by the bodily expressions of the robot and not by the situational context. The findings also show that the perception of *anger* dominance is also biased by the robot's bodily expression and not by the context in which this expression was performed. In addition, the analysis reveal that alignment of a robot's emotionally expressive action and a context enhanced the affective interpretation. Such results suggest that, in a context of a joint human-robot activity, it is possible to use simple emotionally charged movements of a robot to either enhance people's interpretation of a robot's internal status or to provide some additional information that is not obvious from (or may even be contradicting) the situational context.

7.2 Experimental Setup

In this section the independent and dependent variables will be listed and described, as well as the test conditions and the method to analyse the collected data.

The data presented and analysed in this chapter was collected during the experimental study described in the previous Chapter 6.3.6. In this Chapter we will test the hypothesis whether an emotional expression overrides the interpretation of a situational context. We are going to test this on each emotional dimension of valence, arousal and dominance, thus we formulated the three following hypotheses:

- H_V: An emotional expression overrides/biases the interpretation of valence of a situational context.
- H_A: An emotional expression overrides/biases the interpretation of arousal of a situational context.

- H_D: An emotional expression overrides/biases the interpretation of dominance of a situational context.

7.2.1 Experimental Procedure and Participants

This chapter presents the analysis and discussion of the results of the study described in the Chapter 6. The experimental procedure of the study and demographic data of participants were also described in the previous Chapter 6, section 6.3.6.

7.2.2 Independent Variables

The main independent variables in our experiment were *Emotional Expressions* (fear, anger, happiness, sadness and surprise), *Contextual Factor* (only situational context is presented, only emotion is presented, both context and emotion are presented) and *Type of Context* (Appropriate vs Inappropriate). We discuss each of these variables in details below.

Emotional Expressions

We designed and created five emotional expressions for a robot, namely being (1) fearful, (2) angry, (3) happy, (4) sad and (5) surprised. The emotions were selected as a subset of commonly known *discrete* or *basic* emotions, as they were defined by [52]. We used a set of design parameters and their sequences described in the Chapter 6 for creating five emotional expressions in the robot E4. More detailed description of how the expressions were designed are presented in Chapter 6. As a control case, we used in our study a *neutral* emotion when the robot just performed the actions related to its task in different situational contexts and did not perform any additional emotional expression.

For each emotion, we identified one emotional dimension in accordance with a three-dimensional valence-arousal-dominance space proposed by [108] that characterized the chosen emotion the best. This was in order to ensure that the potential effect of context would be examined across all three dimensions. The pilot study was used to identify the most descriptive dimension for each emotion. The associations between each emotion and a corresponding most descriptive emotional dimension are presented in the Table 7.1.

Type of Context

We linked a situational context in which the robot was acting to the three emotional dimensions of valence, arousal and dominance. For each emotional dimension, we created a positive, negative and neutral context. For creating the context of a positive

Expressed Emotion	Descriptive Dimension
fear	Dominance / Negative (D-)
anger	Dominance / Positive (D+)
happiness	Valence / Positive (V+)
sadness	Arousal / Negative (A-)
surprise	Arousal / Positive (A+)

Table 7.1: *Five emotions with the associated most descriptive emotional dimension.*

valence something positive happened in the robot's environment, e.g. the robot managed to finish its task successfully. For the context of a negative valence, something negative happened in the environment after one of the robot's actions, as presented in the Table 7.2. In this thesis, dominance is conceptualized as the degree of control an agent has in order to carry out desired actions. Consequently, a dominance condition is achieved by changing the degree of control. For the study, we mapped this idea to the arrival of an object in the robot's environment over which it would have either great control (positive dominance) or little control (negative dominance) in carrying out its work. Similarly, context was linked to both positive and negative arousal, where the context of positive arousal was associated with a sudden change in the robot's environment and negative arousal of the context was associated with a situation, where the robot does not need to perform any task-related actions.

Emotional Dimension	Associated Situational Context
Positive Valence (V+)	Robot finishes its task successfully.
Negative Valence (V-)	All the blocks fall and scatter immediately after the robot has performed a task-relevant behaviour in the environment.
Positive Arousal (A+)	A block suddenly falls down from above in front of a robot.
Negative Arousal (A-)	The task is already finished, robot's help is not needed.
Positive Dominance (D+)	A dangerous big obstacle prevents a robot from completing a task.
Negative Dominance (D-)	A harmless small obstacle prevents a robot from completing a task.

Table 7.2: *Designed situational contexts with the associated most descriptive emotional dimension.*

The neutral context was used as a control case and was the same for all the dimensions: it meant that nothing had happened in the robot's environment.

In our study, we combined each situational context with a specific emotional expression of the same and the opposite level of the appropriate dimension, e.g. the context of a positive valence was combined with the robot emotional expression of a positive

Emotion	Appropriate Context	Inappropriate Context	Neutral Context
fear	D+	D-	0
anger	V-	V+	0
happiness	V+	V-	0
sadness	A-	A+	0
surprise	A+	A-	0

Table 7.3: *The combination of each emotion expressed by a robot and an appropriate/inappropriate/neutral context. Here, A+,V+,D+ means a context of a positive arousal, valence, dominance, A-,V-,D- means a context of a negative Arousal, Valence, Dominance.*

valence and a negative valence. If the sign of the context emotional dimension matches the sign of the robot expressed emotion, we called such a context an appropriate context for this specific emotion, e.g. the context of a positive valence is an appropriate context for the expression of happiness or the context of a positive arousal is an appropriate context for the expression of surprise. If the sign of the context was opposite to the sign of a presented robot's emotional expression, we called such a context inappropriate, e.g. the context of a negative valence was inappropriate to the expression of happiness. Table 7.3 presents a combination of each emotional expression and an appropriate/inappropriate/neutral context.

Contextual Factor

We controlled a presence of situational context and each emotional expression of the robot in the videos provided to the observer, thus contextual factor is another independent variable in our study. We had three levels of this variable: (1) only a situational context is presented to an observer, later in this chapter named 'Context only', (2) only an emotional expression is presented to an observer, context is not present, later in this chapter named 'Emotion only' (3) both a situational context and an emotional expression are presented to an observer, later in this chapter named 'Context + Emotion'.

7.2.3 Test Conditions

To test our hypotheses, participants were asked to rate videos of a robot across twenty one conditions:

- $C^{\{Afraid,Angry,Happy,Sad,Surprised\}}_{NeutralContext}$: five conditions of each expression presented in a neutral context .
- $C^{NeutralExpression}_{\{V+,V-,A+,A-,D+,D-\}}$: six conditions of each context presented with a neutral expression.

- $\mathrm{C}^{Afraid}_{\{D+,D-\}}$: two conditions of an expression of fear in an appropriate and inappropriate context.
- $\mathrm{C}^{Angry}_{\{V+,V-\}}$: two conditions of an expression of anger in an appropriate and inappropriate context.
- $\mathrm{C}^{Happy}_{\{V+,V-\}}$: two conditions of an expression of happiness in an appropriate and inappropriate context.
- $\mathrm{C}^{Sad}_{\{A+,A-\}}$: two conditions of an expression of sadness in an appropriate and inappropriate context.
- $\mathrm{C}^{Surprised}_{\{A+,A-\}}$: two conditions of an expression of surprise in an appropriate and inappropriate context.

7.2.4 Dependent Variables

Our dependent variables included emotional ratings of robot expressive behaviours based on perceived emotional dimensions of Valence, Arousal and Dominance.

Perceived Valence, Arousal and Dominance

Participants rated a perceived valence, arousal and dominance of robot expressive behaviours with a validated questionnaire called the Self Assessment Manikin (SAM). More information about this tool appears in Chapter 3, section 3.4.3, explaining that SAM is commonly used to rate the affective dimensions of valence, arousal and dominance associated with a person's affective reaction to a wide variety of stimuli. The advantage of a SAM tool is that it is fast to administer and is not subject to language misinterpretations.

Recognition Ratio

Participants were asked to select an emotional term based on their recognition of the emotion expressed by a robot. We offered participants seven terms to select from: afraid, angry, happy, sad, surprised, not emotional, other. The measure used to obtain results for this research question was the recognition ratio $r(p_i, e_j)$ for each expression, which was calculated as defined by Eq. 7.1.

$$r(p_i, e_j) = \frac{N_{ij}}{N} \tag{7.1}$$

where p_i = expression number i , e_j = emotional code number for the specific emotion j; N_{ij} = number of responses (p_i, e_j); N = total number of respondents.

7.2.5 Data Analysis

The conditions $\mathrm{C}^{\{Fear,Anger,Happ.,Sadness,Surprise\}}_{NeutralContext}$ listed in the Section 7.2.3 provide the base interpretation for the respective emotional expressions without any situational context. Similarly, conditions $\mathrm{C}^{NeutralExpression}_{\{V+,V-,A+,A-,D+,D-\}}$ obtain the base interpretation for the situational contexts, which is neccesary before we can measure the relative influence of the context on the perception of emotional expressions. Conditions $\mathrm{C}^{Fear}_{\{D+,D-\}}$, $\mathrm{C}^{Anger}_{\{V+,V-\}}$, $\mathrm{C}^{Happiness}_{\{V+,V-\}}$, $\mathrm{C}^{Sadness}_{\{A+,A-\}}$ and $\mathrm{C}^{Surprise}_{\{A+,A-\}}$ assess the interaction between the emotional expression and the context when combined.

Relating these conditions to the hypotheses, if hypotheses are rejected, it would be expected that, for example, the ratings for $\mathrm{C}^{Anger}_{NeutralContext}$ and C^{Anger}_{V-} would be significantly different while C^{Anger}_{V-} and $\mathrm{C}^{NeutralExpression}_{V-}$ would have similar ratings. It would mean the situational context has been able to pull the rating of the emotion away from the original interpretation. Conversely, if hypotheses are supported, the opposite would be expected: the ratings for C^{Anger}_{V-} and $\mathrm{C}^{NeutralExpression}_{V-}$ would be significantly different while $\mathrm{C}^{Anger}_{NeutralContext}$ and C^{Anger}_{V-} would have similar ratings. In this case the emotional expression has been able to pull the rating of the context away from its original interpretation. These two examples are shown graphically in the Figure 7-1. The ratings here are the scores of perceived Valence, Arousal or Dominance.

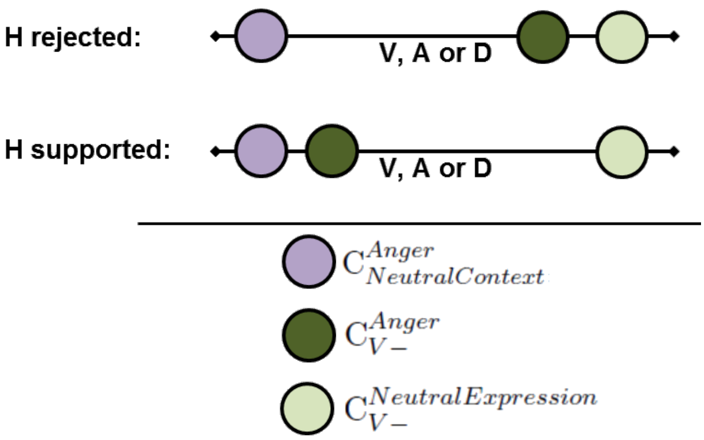


Figure 7-1: *Example of how the video conditions $C^{Anger}_{NeutralContext}$, C^{Anger}_{V-} and $C^{NeutralExpression}_{V-}$ may hypothetically be rated, for each of the two hypotheses.*

Cronbach's α is used as a measure of internal agreement between subjects. For the videos showing only the context the α value for the ratings was 0.835, and for the videos showing only the emotional expressions the α value was 0.607. The ratings for the videos showing the combinations of the context and emotional expressions, the α value for the ratings was 0.708. All these α values are acceptable, indicating a good level of internal agreement between all subjects across all the scenarios and respective video conditions.

Repeated measures ANOVA was used as a statistical test for evaluating an influence of a contextual presence and a type of context on subjects' perception of a robot expressing each of five emotions. We also analysed how the appropriateness of a context influenced the recognition ratio of each presented emotional expression.

7.3 Results

We conducted several tests of repeated measures ANOVA with a factor of Contextual Presence (Context Only, Emotion Only, Context+Emotion) for both appropriate and inappropriate contexts to analyse an influence of of a contextual presence on he perception of robot's expressed Valence, Arousal and Dominance.

7.3.1 Emotion Only Videos

In this section, we present the statistics on perceived valence, arousal and dominance for the emotion-only videos. If the values of perceived emotional dimensions differ significantly, this shows participants are able to recognize and distinguish between different expressive behaviours. The results show that participants recognize the expressive behaviours of the robot in the way they were designed to be interpreted.

The repeated measures ANOVA identified a significant difference between the valence ratings of emotional expressions performed by the robot without any situational context ($F(4, 124) = 9.13$, $MSE = 7.69$, $p<0.001$). This confirms that emotional expressions are interpreted differently in terms of valence, which is a prerequisite for further experiments. The post-hoc tests using the Bonferroni correction revealed that the expression of happiness (mean = 0.56, SD = 1.27) was rated significantly higher on the Valence scale than any other emotional expression ($p<0.005$ for comparison with sadness, anger and fear, $p<0.05$ for comparison with surprise), as shown in upper left part of the Figure 7-2.

	Valence		Arousal		Dominance	
	Mean	StDev.	Mean	StDev.	Mean	StDev.
fear	-0.75	0.88	0.87	0.81	-0.63	1.19
anger	-0.38	1.07	0.74	0.73	-0.13	1.01
happiness	0.56	1.27	0.87	0.92	0.20	1.32
sadness	-0.44	0.91	-0.48	1.00	-0.70	1.02
surprise	-0.25	0.80	0.16	1.00	-0.53	0.90

Table 7.4: *Table showing the mean and standard deviation for the perceived Valence, Arousal and Dominance ratings for each of five emotional expressions.*

The ANOVA tests identified a significant difference between both the arousal ratings ($F(4, 120) = 917.61$, $MSE = 10.8$, $p<0.001$) and the dominance ratings ($F(4, 116)$

= 4.23, MSE = 4.39, p<0.005) of emotional expressions performed by the robot without any situational context. This confirms that emotional expressions are interpreted differently in terms of arousal and dominance which is a prerequisite for further experiments. The post-hoc tests showed that in case of arousal, the expression of sadness received the lowest ratings (mean = -0.48, SD = 1.00) which was significantly lower than for any other emotional expression (p<0.001 for comparison with fear, anger and happiness, p<0.05 for comparison with surprise), as shown in upper right part of the Figure 7-2. In case of dominance, the post-hoc tests only showed a significant difference (p<0.05) between the higher ratings of happiness (mean=0.20, SD = 1.32) and the lower ratings of sadness (mean = -0.70, SD = 1.02), as shown in bottom part of the Figure 7-2. All the mean ratings of valence, arousal and dominance for each of five emotional expressions are presented in the Table 7.4.

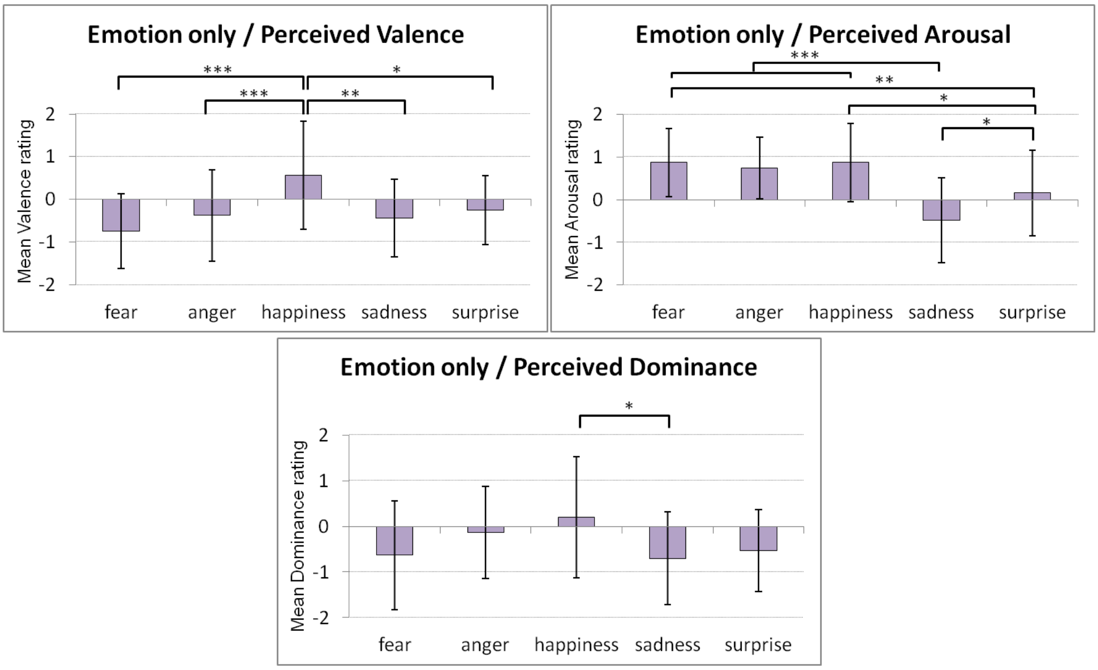


Figure 7-2: *Emotion only manipulations: bar graph showing the mean and standard deviation for the perceived Valence, Arousal and Dominance ratings for each of five emotional expressions.The *** symbol represents p<0.001, ** represents p<0.005, * represents p<0.5*

So, in line with the results of Chapter 6, participants recognized the expressive behaviours in the way they were designed to be interpreted. The fact that there were a more nuanced set of dominance ratings, comparing to valence and arousal ratings, will be considered in Section 7.4.1.

7.3.2 Context Only Videos

In this section, we present the statistics on perceived valence, arousal and dominance for the context-only videos. If the values of perceived emotional dimensions differ significantly, this shows participants are able to recognize and distinguish between different contexts. The results demonstrate that context only videos are entirely neutral in valence, and consistently non-arousing. The ratings of dominance, however, are more nuanced for the context only videos.

The repeated measures ANOVA did not identify a significant difference between the valence ratings of six different situational contexts (F(5, 155) = 0.86, MSE = 0.18, p=0.51). This implies that situational contexts were not interpreted differently in terms of valence. As such, perceived valence will not be used in further experiments. The plot diagram of perceived valence for the six contexts is presented in the bottom part of the Figure 7-3.

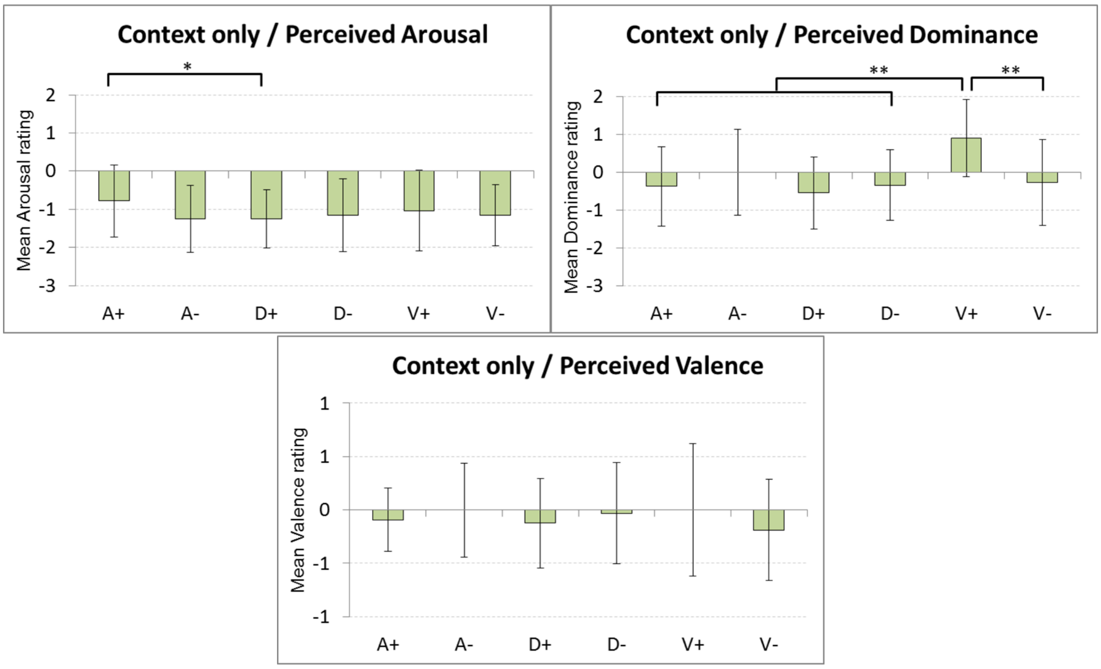


Figure 7-3: *Context only manipulations: bar graph showing the mean and standard deviation for the perceived Valence, Arousal and Dominance ratings for each of six situational contexts.*

The ANOVA tests with Greenhouse-Geisser corrections identified a significant difference between both the arousal ratings (F(3.49, 108.04) = 2.52, MSE = 1.45, p<0.05) and the dominance ratings (F(3.81, 106.64) = 9.50, MSE = 10.47, p<0.001) of different situational contexts. This confirms that situational contexts are interpreted differently in terms of perceived arousal and perceived dominance which is a prerequisite for further experiments. The results showed that in case of perceived arousal, the contexts representing a positive dominance (mean = -1.25, SD = 0.76) and a negative arousal (mean = -1.25, SD = 0.88) both received the lowest ratings. The post-hoc tests revealed a significant difference (p<0.05) between the ratings of perceived arousal for the context representing a positive dominance and the context of a positive arousal, as shown in the upper left part of the Figure 7-3.

In case of perceived dominance, the post-hoc tests showed a significant difference ($p<0.005$) between the highest rating of the context representing a positive valence (mean=0.90, SD = 1.01) and all the other situational contexts, as shown in the upper right part of the Figure 7-3. . All the mean ratings of valence, arousal and dominance for each of six situational contexts are presented in the Table 7.5.

	Valence		Arousal		Dominance	
	Mean	StDev.	Mean	StDev.	Mean	StDev.
$C_{A+}^{NeutrExpr}$	-0.09	0.30	-0.78	0.94	-0.38	1.05
$C_{A-}^{NeutrExpr}$	0.00	0.44	-1.25	0.88	0.00	1.13
$C_{D+}^{NeutrExpr}$	-0.13	0.42	-1.25	0.76	-0.55	0.95
$C_{D-}^{NeutrExpr}$	-0.03	0.47	-1.16	0.95	-0.34	0.94
$C_{V+}^{NeutrExpr}$	0.00	0.62	-1.03	1.06	0.90	1.01
$C_{V-}^{NeutrExpr}$	-0.19	0.47	-1.16	0.81	-0.28	1.13

Table 7.5: *Table showing the mean and standard deviation for the perceived Valence, Arousal and Dominance ratings for each of six situational contexts.*

So, as a baseline test, context only videos are entirely neutral in valence, and consistently non-arousing. The ratings of dominance, however, were more nuanced for both the emotion only and context only videos. For the context only videos, the dominance ratings were moderately positive for the context that was intended to convey positive valence. This difference will be considered in Section 7.4.1.

7.3.3 Emotion/Context combination Videos

This section presents the results of the ANOVA analysis for each of the five emotional expressions individually. The repeated measures ANOVA tests were performed in order to analyse whether contextual information, either appropriate or inappropriate, overrides emotional signal of an expression. As it was explained previously in this chapter, Section 7.2.5, the context overrides emotional signal of an expression if Context-only videos are perceived significantly different from Emotion-only videos, while being perceived similarly to the Emotion+Context videos. Emotional signal of an expression, on the other hand, overrides context if there is a significant difference between the perception of Context-only videos and other two types of videos, while there is no significant difference between Emotion-only and Emotion+Context videos.

The tests were performed for each of five emotional expressions, analysing their perceived arousal and perceived dominance in the case of appropriate and in the case of inappropriate context. The ratings of perceived valence were not analysed, because these ratings were not significantly different in the Context only condition.

The findings of this study supported the hypothesis that an emotional expression overrides the interpretation of a situational context in signalling emotional information.

More specifically, the perception of arousal for the expressions of anger, happiness, sadness and surprise was biased by the bodily expressions of the robot and not by the situational context. The findings also showed that the perception of anger dominance was also biased by the robot's bodily expression and not by the context in which this expression was performed.

Expression of Happiness

The expression of happiness was contrasted with the situational contexts of a positive valence (as appropriate) and negative valence (as inappropriate). For this expression, the ANOVA found a difference in the perceived arousal between the Emotion only, Emotion+Context and the Context only conditions, which was significant both for the appropriate ($F(2, 64) = 44.19$, $MSE = 38.86$, $p<0.001$) and inappropriate context ($F(2, 66) = 75.69$, $MSE = 43.18$, $p < 0.001$). In case of the appropriate context, the Bonferonni post-hoc tests resulted in a significant difference between two pairs of conditions: 1) between the Emotion only condition and the Context only condition ($p < 0.001$), and 2) between the conditions of Emotion+Context and Context only ($p < 0.001$). However, there was no significant difference between the Emotion only condition and the Emotion+Context conditions, as shown in the left part of the Figure 7-4.

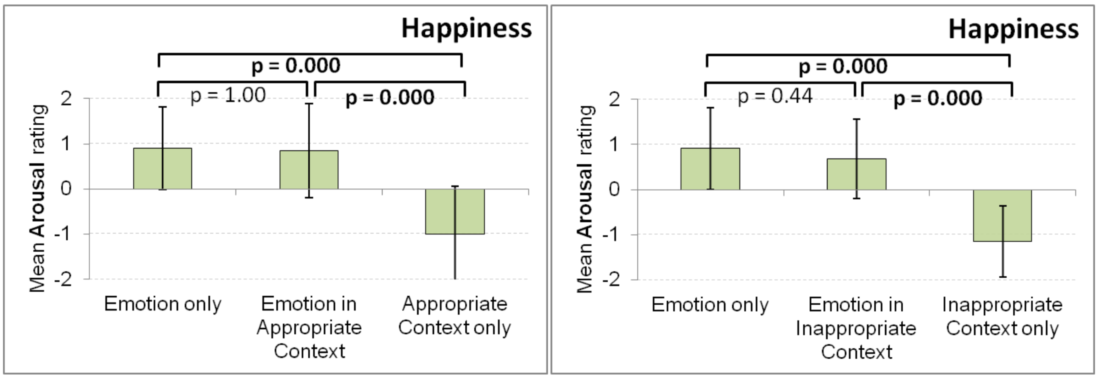


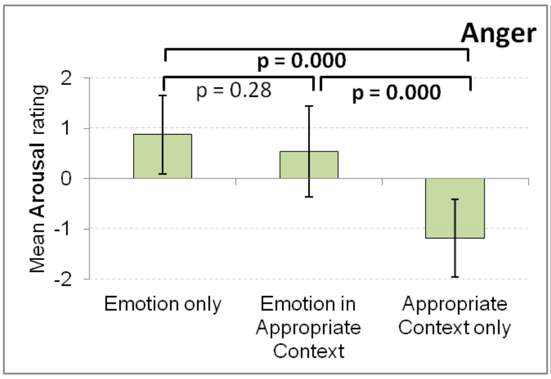
Figure 7-4: *Bar graph showing the mean and standard deviation for the perceived Arousal for the expression of Happiness in three conditions: Emotion only, Emotion+Context and Context only. Left - the case of appropriate context. Right - the case of inappropriate context.*

In case of the inappropriate context, the Bonferonni post-hoc tests also resulted in a significant difference between two pairs of conditions: 1) between the Emotion only condition and the Context only condition ($p < 0.001$), and 2) between the conditions of Emotion+Context and Context only ($p < 0.001$). However, there also was no significant difference between the Emotion only condition and the Emotion+Context conditions, as shown in the right part of the Figure 7-4. Thus, both cases support the H_A hypothesis, stating that the emotional expression of happiness overrides the interpretation of both appropriate and inappropriate situational context when speaking about perceived arousal.

The ANOVA found a significant difference in the perceived dominance ratings between the Emotion only, Emotion+Context and the Context only conditions within the appropriate context ($F(1.4, 44.79) = 12.69$, $MSE = 17.45$, $p < 0.001$). However, the results of the post-hoc Bonferroni tests revealed there was no significant difference between the condition of Emotion only and Context only ($p = 0.07$), thus the results were not used in the analysis. In the case of the inappropriate context, the ANOVA did not find a significant difference between the Emotion only, Emotion+Context and the Context only conditions within the appropriate context ($F(1.6, 51.19) = 2.97$, $MSE = 4.71$, $p = 0.07$).

Expression of Anger

The expression of anger was contrasted with the situational contexts of a positive valence (as inappropriate) and negative valence (as appropriate). For this expression, the ANOVA found a difference in the perceived arousal between the Emotion only, Emotion+Context and the Context only conditions, which was significant both for the appropriate ($F(2, 64) = 56.27$, $MSE = 40.37$, $p<0.001$) and inappropriate context ($F(2, 64) = 34.49$, $MSE = 36.49$, $p < 0.001$). In case of the appropriate context, the Bonferonni post-hoc tests resulted in a significant difference between two pairs of conditions: 1) between the Emotion only condition and the Context only condition ($p < 0.001$), and 2) between the conditions of Emotion+Context and Context only ($p < 0.001$). However, there was no significant difference between the Emotion only condition and the Emotion+Context conditions, as shown in the left part of the Figure 7-5.



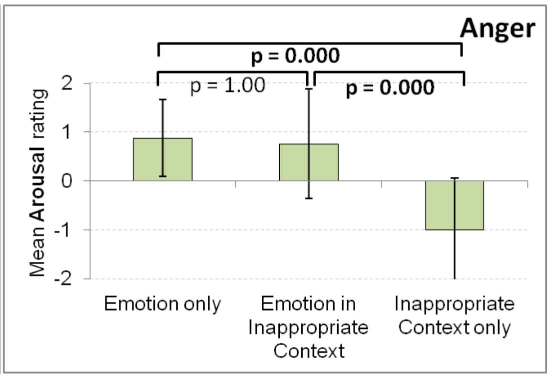


Figure 7-5: *Bar graph showing the mean and standard deviation for the perceived Arousal for the expression of Anger in three conditions: Emotion only, Emotion+Context and Context only. Left - the case of appropriate context. Right - the case of inappropriate context.*

In case of the inappropriate context, the Bonferonni post-hoc tests also resulted in a significant difference between two pairs of conditions: 1) between the Emotion only condition and the Context only condition ($p < 0.001$), and 2) between the conditions of Emotion+Context and Context only ($p < 0.001$). However, there also was no significant difference between the Emotion only condition and the Emotion+Context conditions, as shown in the right part of the Figure 7-5. Thus, both cases support the H_A hypothesis, stating that the emotional expression of anger overrides the interpretation of both appropriate and inappropriate situational context when speaking about perceived arousal.

The ANOVA did not find a significant difference in the perceived dominance ratings between the Emotion only, Emotion+Context and the Context only conditions within the appropriate context ($F(2,60) = 0.44$, $MSE = 0.53$, $p = 0.65$).

Expression of Sadness

The expression of sadness was contrasted with the situational contexts of a negative arousal (as appropriate) and positive arousal (as inappropriate). For this expression, the ANOVA found a difference in the perceived arousal between the Emotion only, Emotion+Context and the Context only conditions, which was significant both for the appropriate ($F(2, 62) = 14.70$, $MSE = 12.01$, $p<0.001$) and inappropriate context ($F(2, 64) = 13.69$, $MSE = 11.49$, $p < 0.001$). In case of the appropriate context, the Bonferonni post-hoc tests resulted in a significant difference between two pairs of conditions: 1) between the Emotion only condition and the Context only condition ($p < 0.05$), and 2) between the conditions of Emotion+Context and Context only ($p < 0.001$). However, there was no significant difference between the Emotion only condition and the Emotion+Context conditions, as shown in the Figure 7-6. Thus, this case supports the H_A hypothesis, stating that the emotional expression of sadness overrides the interpretation of both appropriate and inappropriate situational context when speaking about perceived arousal.

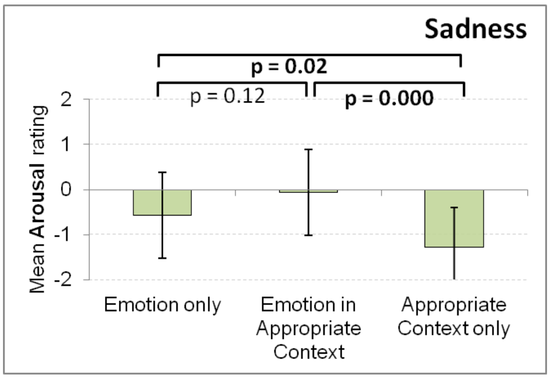


Figure 7-6: *Bar graph showing the mean and standard deviation for the perceived Arousal for the expression of Sadness in three conditions: Emotion only, Emotion+Context and Context only. The plot presents the case of the appropriate context.*

In case of the inappropriate context, the Bonferonni post-hoc tests revealed there was no significant difference between the arousal ratings for the condition of Emotion only and Context only ($p = 0.99$), thus the results were not used in the analysis.

The ANOVA found a significant difference in the perceived dominance ratings between the Emotion only, Emotion+Context and the Context only conditions within the appropriate context ($F(2, 60) = 3.90$, $MSE = 4.29$, $p < 0.05$). However, the results of the post-hoc Bonferroni tests revealed there was no significant difference between the condition of Emotion only and Context only ($p = 0.14$), thus the results were not used in the analysis. In the case of the inappropriate context, the ANOVA did not find a significant difference between the Emotion only, Emotion+Context and the Context only conditions within the appropriate context ($F(2, 60) = 2.16$, $MSE = 1.97$, $p = 0.13$).

Expression of Surprise

The expression of surprise was contrasted with the situational contexts of a negative arousal (as inappropriate) and positive arousal (as appropriate). For this expression, the ANOVA found a difference in the perceived arousal between the Emotion only, Emotion+Context and the Context only conditions, which was significant both for the appropriate ($F(2, 60) = 28.49$, $MSE = 21.43$, $p<0.001$) and inappropriate context ($F(2, 60) = 35.26$, $MSE = 22.33$, $p < 0.001$). In case of the inappropriate context, the Bonferonni post-hoc tests resulted in a significant difference between two pairs of conditions: 1) between the Emotion only condition and the Context only condition ($p < 0.001$), and 2) between the conditions of Emotion+Context and Context only ($p < 0.001$). However, there was no significant difference between the Emotion only condition and the Emotion+Context conditions, as shown in the Figure 7-7.

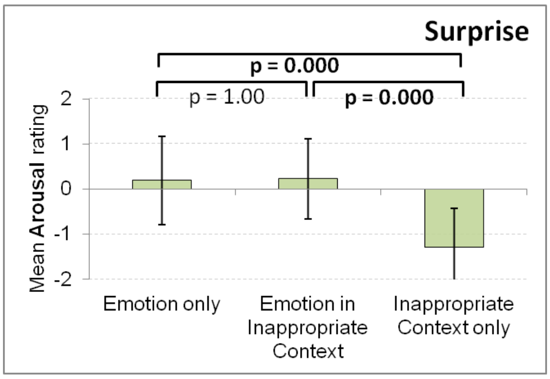


Figure 7-7: *Bar graph showing the mean and standard deviation for the perceived Arousal for the expression of Surprise in three conditions: Emotion only, Emotion+Context and Context only. The plot presents the case of the inappropriate context.*

Thus, this case supports the H_A hypothesis, stating that the emotional expression of sadness overrides the interpretation of both appropriate and inappropriate situational context when speaking about perceived arousal.

In case of the appropriate context, the Bonferonni post-hoc tests revealed a significant difference between all three conditions, thus the results were not used in the further analysis.

The ANOVA did not found a significant difference in the perceived dominance ratings between the Emotion only, Emotion+Context and the Context only conditions within either the appropriate context ($F(2, 58) = 0.50$, $MSE = 0.04$, $p = 0.95$) or inappropriate context (($F(2, 56) = 0.95$, $MSE = 0.93$, $p = 0.39$).

Expression of Fear

The expression of fear was contrasted with the situational contexts of a negative dominance (as inappropriate) and positive dominance (as appropriate). For this expression, the ANOVA found a difference in the perceived arousal between the Emotion only, Emotion+Context and the Context only conditions, which was significant both for the appropriate ($F(2, 64) = 81.05$, $MSE = 49.71$, $p<0.001$) and inappropriate context ($F(2, 62) = 97.31$, $MSE = 60.17$, $p < 0.001$). However, the Bonferonni post-hoc tests revealed there was no significant difference between the the arousal ratings for the condition of Emotion only and Context only in either the case of the appropriate context ($p = 0.31$) or inappropriate context ($p = 1.00$), thus the results were not used in the further analysis.

The ANOVA did not found a significant difference in the perceived dominance ratings between the Emotion only, Emotion+Context and the Context only conditions within either the appropriate context ($F(2, 62) = 1.16$, $MSE = 1.16$, $p = 0.32$) or inappropriate context (($F(2, 62) = 1.76$, $MSE = 1.22$, $p = 0.18$).

7.3.4 Effect of the Context Type on Recognition Ratio

In our study, participants were asked to select an emotional term based on their interpretation of the emotion expressed by the robot. Participants were given seven terms to select from, so the level of a random choice was 0.14. We found that the recognition ratio of the emotions of *fear, anger, happiness and surprise* was higher than the level of a random choice in both the 'Emotion only' and 'Context + Emotion' scenarios.

When only the context was presented to the participants, the recognition ratio did not usually exceed the random choice level. The only exception was the context of a positive arousal, when a block suddenly fell down in front of the robot and the robot didn't react to this event in any way. In this case, 18% of participants selected *surprise* as an interpretation of a robot's emotion, as shown in Figure 7-8.

The recognition ratio of the expression of *sadness* did not exceed the random level in any of tested scenarios, as presented in the left bottom part of the Figure 7-8, so it will not be further analysed.

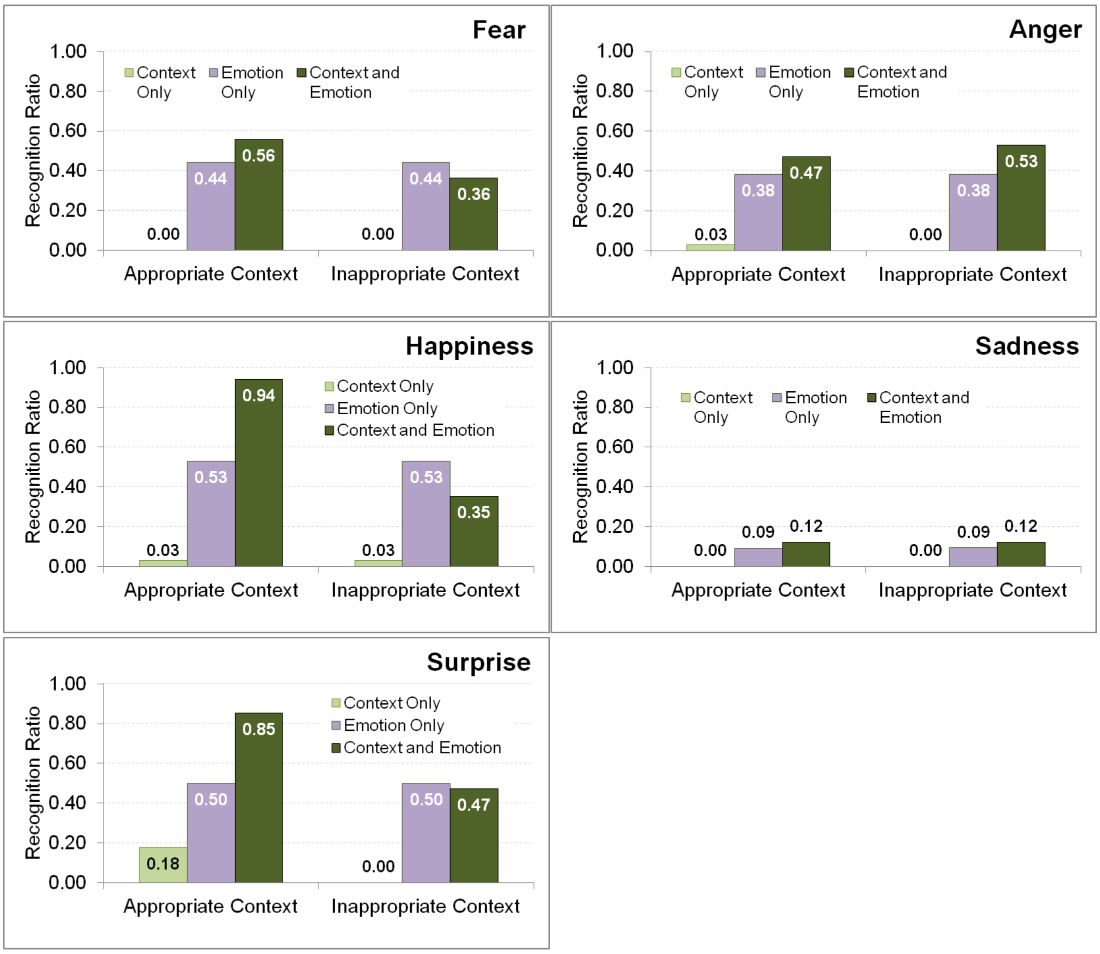


Figure 7-8: *Bar graphs showing the recognition ratio of the emotions of Fear, Anger, Happiness, Sadness and Surprise expressed by the robot in an appropriate and inappropriate context, under different scenarios of contextual presence.*

The results showed that in an appropriate context scenario, the presentation of a context in addition to the emotional expression only increased the recognition ratio of all the tested emotional expressions. The increase was the highest for the expressions of *happiness*, where the recognition ratio increased by 0.41 comparing an 'Emotion only' scenario (r=0.53) and 'Context + Emotion' scenario ($r = 0.94$), and for the expression of *surprise*, where the recognition ratio increased by 0.35 comparing an 'Emotion only' scenario (r=0.5) and 'Context + Emotion' scenario ($r = 0.85$). For the emotional expressions of *fear* and *anger*, the increase was respectively 0.12 and 0.09.

Within an inappropriate context, the recognition ratio decreased for the emotional expressions of *fear, happiness* and *surprise*. The decrease was the biggest for the expressions of *happiness*, where the recognition ratio decreased by 0.18 comparing an 'Emotion only' scenario (r=0.53) and 'Context + Emotion' scenario ($r = 0.35$). For the emotional expressions of *fear* and *surprise*, the decrease was respectively 0.08 and 0.03. For the emotional expression of *anger*, adding inappropriate context increased the recognition ratio from 0.38 in the 'Emotion only' scenario to 0.53 in the 'Context + Emotion' scenario.

All the results of recognition ratios for each emotional expression are presented in the Figure 7-8.

7.4 Discussion

This section provides a discussion of the study and obtained results from several perspectives, such as with regard to our hypotheses outlined in the beginning of this Chapter and the implications of how a robot's emotional expressions should be designed within different contexts.

We implemented the expressions of five basic emotions in combination with different types of context. Let us examine whether the results of the study supported our hypotheses.

7.4.1 Main Effects

The acceptable values of Cronbach's α provide confidence regarding the validity of the results of perceived valence, arousal and dominance, obtained via the SAM questionnaire.

The findings of our study reveal that the interpretation of dominance in the emotion only and context only conditions differed from the interpretation of valence and arousal. In the emotion only condition, the ratings of valence and arousal were different across different emotional states expressed by the robot. The difference between the ratings of dominance, although significant in some cases, was smaller. In the context only videos, the ratings of dominance for the context representing positive valence, was moderately positive, compared to neutral ratings of dominance collected for other contexts. We tried to explain these nuances by analysing how the dispersion of the ratings of valence, arousal and dominance in both emotional only and context only conditions. The results of such analysis showed that the dispersion of the ratings of all three dimensions were in the range between 0.5 and 0.6 for the emotion only videos, while this range was smaller (from 0.1 to 0.4) for the context only videos. This lets suggest that the significantly higher ratings of perceived dominance in the context of positive valence do not change the general suggestion that the ratings of context only videos were all on a similar level, differently from the emotion only videos.

The findings of our study supported the second hypothesis stating that "an emotional expression overrides/biases the interpretation of a situational context". This hypothesis was supported by the results of ANOVA tests for the expressions of anger, happiness, sadness and surprise. The findings showed that the perception of these emotions' arousal was biased by the bodily expressions of the robot and not by the situational context. This was true for the appropriate situational context in cases of anger, happiness and sadness. In cases of surprise, anger and happiness, this hypothesis was also supported in the case of inappropriate situational context. In addition, the findings showed that the perception of anger's dominance was also biased by the robot's bodily expression and not by the context in which this expression was performed.

The interpretation of the 'Context + Emotion' conditions was significantly different from the interpretation of the 'Context only' conditions when interpreting valence and arousal of the emotional robot expressions of fear, anger, happiness and surprise. Thus, the results of our study did not provide evidence supporting the potential assumption that the situational context overrides the interpretation of emotional expression of a robot, in contrast to some previous research [141]. We assume that such a contradiction in results could be due to very different modalities of emotional expressions used in our study and in the study of [141]. Further research is required to test this assumption.

However, our findings do correspond to the results of [141] in the part stating that alignment of robot's action and affective context enhanced the affective interpretation. Our findings revealed that adding an appropriate context to the robot's emotional expression increases the recognition ratio of all the designed emotions, some of them notably, e.g. the recognition of happiness increased from 53% to 94% with an addition of an appropriate context. These findings also correspond to the preliminary results of [14].

7.4.2 The Definition of Context

In this study, situational context was treated as the robot's environment that has the potential to facilitate or inhibit its ability to carry out its work. One could argue this means that situational context does not have any emotional colouring by itself and this is the reason why it does not influence the interpretation of robot emotional expressions. We do not agree with such an interpretation and provide two reasons for this.

First, we argue that the experimental briefing was designed to set expectations about the meaning of the environment for robot action. So any interpretation of the state of the environment would have been in terms of an observer's beliefs about what would be obstructive or helpful for the robot. More importantly still, the meaning of situation in this research is inextricably linked to the progress of a robot's work. So the environment sets the context for the physical tasks the robot will attempt to carry out and the concept of situation is clarified this way. Thus, even when the robot does not react in any way to the situation of a brick falling suddenly in front of it, this does not mean that the observer interprets the situation as neutral. The results, presented in section 7.3.2, support our argument by showing significant difference between observers perception of context-only videos in terms of arousal and dominance.

Second, we argue that robot inaction in the situations when it does not react to the changes in its environment, is not meaningful for an observer. In contrast with the other actions an observer has seen the robot carry out, inaction could be seen as the result of a robot's internal state, i.e. a decision not to act, rather than the failure to take a decision. So, we reject the assertion that an observer must necessarily see nothing of emotional significance if they observe a robot in a passive state. Judgements are never made in a vacuum. The fact that observers were required to make a series of judgements would mean that they could attribute an emotional state to a robot that has not enacted an expressive behaviour, by contrast with other matters.

To summarise, the definition of situational context may be interpreted in several different ways that may potentially generate methodological problems in human-robot interaction studies. However, the potential methodological problems can be overcome by an appropriate study design, as done in the study presented in this chapter.

7.4.3 Design Recommendations

The results of our study provide specific design recommendations and insights as to how emotional robot expressions may be used practically in both real-world settings and future experimental scenarios.

Perceived valence, according to the findings of our study, is not induced by context but by a robot emotional expression. The study results showed that no matter what context was presented to observers they tended to score it with a neutral valence. With an addition of an emotional expression, the scores of perceived valence changed in accordance to the expressed emotion. The perception of valence was not changed significantly by adding a context to an emotional bodily expression. Thus we would recommend to control the perception of valence in human-robot interactions by positive and negative bodily expressions of a robot.

As a general "rule of thumb", it is likely that a robot acting in a neutral way will induce a perception of negative arousal in observers even when something unexpected, sudden or uncontrolled is happening. In order to change it to a positive level, robot should visually react to the changes in the environment. Our findings showed that emotional bodily expressions are a good way to react to different stimuli and thus convince observers of a higher level of robot arousal. Adding a situational context to the emotional expression of a robot does not change significantly the proper perception of arousal, and can even confuse observers if the context is not selected carefully.

The findings of our study reveal that people tend to assess robot dominance as negative both when it is expressing emotions with its body in a context-free situations and when acting in a neutral way in context-specific scenario. However, with an appropriate context the perceived dominance increases in (1) the positive scenarios, and (2) the scenarios where robot body language expresses a high level of control over the situation. Thus, in experimental settings we would recommend to design an appropriate contextual information when a robot is supposed to communicate higher dominance to a person. In real-world settings, we would recommend to carefully align the stimuli triggering robot emotions with appropriate emotional expressions that are supposed to communicate higher dominance.

Our findings show that most emotional dimensions can be communicated by a robot and properly interpreted by observers without the help of additional appropriate context, even in the situation of an inappropriate context. As we discussed earlier, the findings of our study clearly showed that context did not override the emotional signal sent by a robot's bodily expression. However, when trying to convey a specific basic emotion using robot's body language, we would recommend to present an emotional expression in a situation of appropriate context. The results of our study show that adding an appropriate context helps increase the recognition ratio of all the five tested basic emotions.

7.5 Conclusions

We attempted to address a gap in the literature and presented a study on interaction between situational context and emotional body language in robotics.

In our experimental study, participants were shown 21 video conditions, showing a robot expressing five basic emotions in different contexts. For each video, the participants rated their perception of robot's valence, arousal and dominance and guessed the emotion expressed by a robot. In general, the findings of this study supported the hypothesis that an emotional expression overrides the interpretation of a situational context in signalling emotional information. The results suggest that emotional bodily expressions of a robot influence observers' perception of its valence and increase the perception of arousal. Together with appropriate contextual information, emotional bodily expressions of a robot change the perception of its dominance in observers. In addition, appropriate contextual information helps to increase the recognition ratio for five tested basic emotions of fear, anger, happiness, sadness and surprise.

We also have discussed design guidelines regarding how emotional body language of a robot can be used in different contexts by roboticists developing social robots. For example, we recommend to use emotional bodily expressions to induce a required valence of a robot, as otherwise it is very likely for the robot to be perceived as neither positive or negative independent of the context.

In this chapter, we have discussed how the particular situational context in which emotional expressions are used by a robot influence how they are perceived and interpreted by people. Another major factor to investigate is how the morphology of a robot performing emotional expressions influences how these expressions are interpreted. The next chapter will focus on the impact of robot body form in interpreting its emotional bodily expressions thus validating the design scheme presented earlier in Chapter 6 on different robot form factors.

CHAPTER 8

VALIDATING THE DESIGN SCHEME ON ROBOTS OF DIFFERENT EXPRESSIVITIES

8.1 Introduction

In Chapter 6 we presented an integrated account of the effect of a range of characteristics of robot movement on human perception of affect. We used anatomical body planes as a reference for combining research on animal social behaviour with Shape and Effort dimensions derived from the Laban theory of movements to present a scheme for designing emotionally expressive robotic behaviours. The scheme includes two concepts to define emotionally expressive behaviours for robots: Expressive Shape and Expressive Quality. Expressive Shape defines how the overall posture of a robot should change in terms of its physical form, and relates this change to the emotional significance of approach and avoidance in the animal world. The scheme is presented in Table 8.1 and it is associated with ten distinct parameters of body motion. Expressive Quality defines the performative characteristics of robot movement, i.e. strength or frequency, again grounding the meaning of these characteristics in prior work on signals of affective state in animals and people, as discussed previously in Chapter 2, section 2.2.3. It is associated with a further thirteen parameters of motion. The general grounding of the scheme is intended to reflect its generality in application for different types of non-humanoid robots. In the previous Chapter 7 the scheme has been validated in a design context. However, it does not explain how this design scheme might be implemented with different forms of non-humanoid robots. Thus in this current Chapter we introduce a new concept of a robot *expressivity* that allows us to further generalize the earlier proposed scheme for designing expressive behaviour and validate it with two very different types of robots.

It is common for non-humanoid robots to vary greatly in terms of the number of embodied degrees of freedom, and the maximum amplitude, velocity and frequency of motions they are able to perform. However, there are some similarities in the influence of the parameter on perceived dimensions of emotional meaning, e.g. higher speed of expressive movement often increases perceived level of arousal, or that reduction of size (shrinking) can reduce the perceived level of dominance. Thus, it may be that all robots are capable of expressing basic emotional states, regardless of their form factor, as long as their behavioural capabilities are mobilised appropriately.

In this Chapter, we investigate the form of the robot as a potential factor that could influence how people interpret the emotionally charged bodily expressions of a robot. Thus we are addressing the third research question of this thesis, formulated as follows: "RQ3: What factors impact how people interpret the emotionally charged bodily expressions of a robot?". From a design perspective, we propose that all robots can be described in terms of their general *expressivity*, whilst still being able to convey emotional meaning through their movement. As a property, we argue that expressivity refers to aspects of the construction of a robot that constrain the robot's ability to vary in terms of Expressive Shape and Expressive Quality. This leads us to our first hypothesis:

H1. Perceptions of emotionally expressive movements do not vary as a function of the degree of a non-humanoid robot's expressivity.

We provide a detailed description of expressivity as it applies to this study in the method section, so that its treatment as an independent variable is clear. The second hypothesis analysed in this chapter is formulated as follows:

H2: An observer's beliefs about the successfulness of robot's actions varies consistently with the nature of the robot's expressive behaviour.

In this chapter, we treat beliefs about successfulness through the two complementary observer ratings: judgement of whether the robot successfully completed its task, and judgement of the robot's intention to continue or abandon its current activity.

The results of the study reported in this chapter show both the similarities and differences in the perception of valence, arousal and dominance after applying the design scheme to non-humanoid robots of different expressivity. In terms of similarities, some design parameters, such as high energy level or avoidance, have a similar influence on observer perceptions of valence, arousal and dominance for both forms of robot i.e. regardless of robot expressivity. Some other design parameters, such as intensity, have a different influence on perceived emotional dimensions. For example, low intensity increases the level of perceived valence in the robot of low expressivity and decreases it in the robot of high expressivity. The findings of the study also reveal that both the rating of robot successfulness and the ratings of robot intention vary significantly depending on its expressive movements.

The results of this work suggest that in many cases the form factor of a robot does

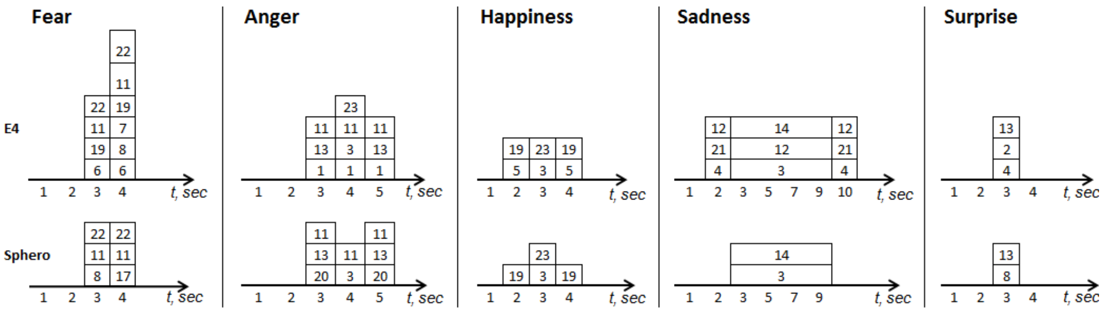


Figure 8-1: *The combination of design parameters for the emotional expressions of fear, anger, happiness, sadness and surprise, as implemented in a more expressive E4 robot (top) and a less expressive Sphero robot (bottom).*

not impact the people's interpretations of robot expressive behaviour, although the HRI designers should be aware of some potential differences.

8.2 Method

We designed a mixed-model experiment, in which participants observed and rated video clips of a robot in action. We used a between-subject design for presenting clips of two different robots - a more expressive non-humanoid robot E4 (for more details on the robot, see Chapter 3, section 3.3.1) with several limbs for the first group of participants and a less expressive abstract robotic ball Sphero (for more details on the robot, see Chapter 3, section 3.3.2) for the second group. Within each group, we used a within-subject design for presenting subjects with a sequence of expressive behaviours performed by their respective robot.

8.2.1 Classifying Robot Expressivity

We refined and generalized the scheme proposed in the Chapter 6 for designing emotional body language in our robots. The scheme is shown in Table 8.1 and it presents a hierarchical system of design characteristics combined into two large movement groups: *Shape* and *Quality*. The lowest level of the scheme consists of 23 parameters. We link each parameter of the *Shape* group to the capability of a robot to move its body in a specific way, depending on its construction. We also linked each parameter of the *Quality* group to an ability to control robot actions in a specific way. The list of *Shape* and *Quality* design parameters (DPs) with an associated ability to program robot movements are listed in the right-hand part of Table 8.1.

The list of expressive parameters allows us to define the level of expressivity for any type of robot simply by summing the parameters that can be activated in a specific robot. Thus, the maximum expressivity level for any type of robot is determined by its ability to make use of all 23 parameters. This is a simplistic method for contrasting the base expressivity of any form of robot since it does not privilege any particular parameter. It may be that specific parameters of Expressive Quality or Expressive Shape, or combinations thereof, invoke higher emotional significance. We shall return to this point in our general discussion.

Each design parameter is associated with one or several emotions, as we have discussed previously in the Chapter 6, section 6.2. Thus, the higher a robot's expressivity, the greater its potential ability to express emotion through body language.

8.2.2 Emotional Expressions

We created five emotional expressions for the robots, namely: (1) fearful, (2) angry, (3) happy, (4) sad and (5) surprised. The emotions were selected as a subset of commonly known *discrete* or *basic* emotions, as defined by [52]. We used design parameters shown in Table 8.1 to create emotional expressions in robots, based on the mapping from animal behaviours to general parameters of body movement. We were able to make use of more design parameters for creating expressions in the high expressivity robot E4 than in the less expressive Sphero because of differences in their construction. One of the contributions of this chapter is to demonstrate how a general scheme for designing robot emotional expressions can be mapped to non-humanoid robots with very different expressive possibilities. The precise mappings require the designer to exercise judgement, as it true of all design, but the general scheme does not privilege any particular parameter. Thus, design freedom is preserved for at least basic emotions. Figure 8-1 presents the combinations of design parameters used for creating each emotional expression in both robots, where block numbers correspond to the ID numbers allocated to design parameters and the horizontal axis represents time of onset and offset in seconds. For example, to create an expression of happiness in the Sphero robot, we used a parameter No. 19 (vibration at a high level) at two seconds, parameters No. 3 and 23 at three seconds (moving forward in a curved trajectory), and parameter No. 19 (fast vibration) at four seconds, creating an expressive behaviour that lasted for three seconds in total. As seen from the Figure 8-1, both robots use the same initial DPs for expressing each of five basic emotions e.g. parameters No. 8, 11 and 22 for expressing Fear; 3, 11 and 13 for expressing Anger etc. Such a similarity in designing emotional expressions makes the comparison of the movements valid although the capabilities of the actuators are very different in two presented robots.

8.2.3 Independent Variables

The two main independent variables in our experiment were *expressivity* of robot (high expressivity vs. low expressivity), *Design Parameter group* (approach/avoidance; high/low energy; high/low intensity; high/medium/low frequency). We also varied the influence the occurrence of positive and negative events in the robot's environment

SHAPE:

Group	ID	Parameter Name	Body Part or Ability
Approach	1	Transfer weight forward	ability to bend or bow forward
Approach	2	Move limbs forward	movable limbs
Approach	3	Move its body forward	wheels, tracks, legs. Roll, fly, swim, drive, go, move the body forward
Approach	4	Move visible appendage(s) away from the body	movable limbs, visible movable appendage(s) not used for moving forward/backward, movable head
Approach	5	Extend or expand its body	ability to extend or expand itself
Avoidance	6	Transfer weight backward	ability to bend or bow backward
Avoidance	7	Move limbs backward	movable limbs
Avoidance	8	Move its body backward	wheels, tracks, legs. Roll backward, fly backward, swim backward, drive backward, go backward, move the body backward
Avoidance	9	Attract limbs close to the body	movable limbs, visible movable appendage(-s) not used for moving forward/backward, movable head
Avoidance	10	Reduce its body	ability to reduce itself

QUALITY:

Group	ID	Parameter Name	Ability to Program
Energy	11	High strength	motor's speed at high level
Energy	12	Low strength	motor's speed at low level
Intensity	13	Sudden	sudden start/finish
Intensity	14	Not sudden	smooth start/finish
Flow	15	Short duration	movement able to finish in a short time
Flow	16	Medium duration	movement able to finish in a medium time
Flow	17	Long duration	movement able to finish in a long time
Flow	18	High change in tempo	motor's speed change
Flow	19	High frequency	high level of vibration, spinning or frequent movements of the limbs
Flow	20	Medium frequency	medium level of vibration, spinning or frequent movements of the limbs
Flow	21	Low frequency	low level of vibration, spinning or frequent movements of the limbs
Flow	22	Direct trajectory	straight, linear, direct movement of the whole body
Flow	23	Indirect trajectory	curved movement of the whole body

Table 8.1: *Parameters of a* Shape *(top) and* Quality *(bottom) group with associated robot's programming abilities.*

to examine the *consistency of emotional ratings* as an indication of the robustness of expressive behaviours (consistent; inconsistent; not emotional).

Robots We used two robots in our experiment: E4 and Sphero (see Chapter 3, Figures 3-2 and 3-4).

Robot with Higher Level of Expressivity. The more expressive robot, E4, was implemented with Lego Mindstorms NXT (for more details on the robot, see Chapter 3, section 3.3.1). The robot had two motors which allowed it (1) to move forwards and backwards on a surface, (2) to move the upper part of its body. The upper body part was constructed such that the robot's hands moved together with its neck and eyebrows. Its neck could move forwards and backwards, and its hands and eyebrows could move up and down. The overall expressivity level of the E4 robot is 19. The RWTH Mindstorms NXT Toolbox for MATLAB [1] was used to program E4's behaviours.

Robot with Lower Level of Expressivity. The less expressive robot, Sphero (for more details on the robot, see Chapter 3, section 3.3.2), is a robotic ball [2] with a ARM Cortex M4 processor, two RGB LEDs and two internal motors that allowed it (1) to roll on a surface at different speeds and directions, (2) to spin or vibrate at different frequencies. Although it is also possible to change Sphero's colour, we did not use this function in our study. The overall expressivity of the Sphero robot was 12.5. We used the Android SDK provided by Sphero[3] to program Sphero's rolling direction, speed and directional pattern. We used a Samsung TabPRO 8.4 tablet to control Sphero via Bluetooth for creating the video clips.

Design Parameters (DPs)

Four groups of design parameters (DPs) were used as independent variables in our study. For the high-level group of *Shape*, we used *Approach* and *Avoidance* DPs. For the high-level group of *Quality*, we used low and high *Energy*, low and high *Intensity* and low, medium and high *Frequency*, which is a sub-level of the *Flow* group.

Consistency of Emotional Ratings We recorded a set of videos where an event in the robot's task environment was combined with a specific emotional expression of the same and the opposite level of the appropriate dimension, e.g. an event of a positive valence was recorded with the robot expressing an emotion of a positive valence, of negative valence and a neutral one. If the sign of context's emotional dimension matched the sign of a robot's expressed emotion on the same dimension, we treated the emotion as *consistent*. If a sign of the context was opposite to the sign of a presented robot's emotional expression, we treated it as *inconsistent*. If robot only performed the actions related to its task and didn't perform any emotional expression in addition, we called such an emotion *neutral*.

[1] http://www.mindstorms.rwth-aachen.de/
[2] http://www.gosphero.com
[3] https://github.com/orbotix/Sphero-Android-SDK

8.2.4 Test Conditions

We recorded five emotional expressions performed by each robot in a neutral environmental context. In addition, we recorded eighteen combinations of each context and a consistent, inconsistent and neutral emotion. Five emotional expressions without context plus eighteen combinations of a context and a consistent/inconsistent/neutral emotional expressions resulted in a list of twenty three emotional expressions of each robot in different contexts, each of the duration of 3-13 sec.

8.2.5 Dependent Variables

Our dependent variables included emotional ratings of robot expressive behaviours; ratings of robot task intention, and ratings of robot task success. We also collected demographic information on age and gender.

Perceived Emotional Dimensions Participants rated valence, arousal and dominance of robot expressive behaviours with a validated questionnaire called the 'Self assessment manikin' (SAM) [20]. SAM has been used to rate the affective dimensions of valence, arousal and dominance in a wide variety of settings [20].

Judgement of Robot Intentions Judgements of robot intentions were scored on a 5-point Likert scale, in response to the question *Do you think the robot is going to continue its task?* The score 1 means *'Definitely not going to continue'* and score 5 means *'Definitely going to continue'*.

Judgement of Robot Task Success Judgement of task success was again scored on a five-point Likert scale, in response to the question *Do you think the robot's task was completed successfully?* The scale ranged from *Definitely No*, which was equal to the rating of 1, to *Definitely Yes*, equal to the rating of 5.

8.2.6 Experimental Procedure and Participants

We used a between-subject design for the robot expressivity variable. 34 participants (9 females and 25 males; age from 18 to 46, M=23.21, SD=7.42) rated video clips of the high-expressivity E4 robot. 20 participants (7 females and 13 males; age from 23 to 38, M=29.25, SD=3.60) were assigned to the low-expressivity Sphero robot .

A within-subject design was used to assign participants to a specific task condition, i.e. each participant was exposed to all the twenty-three experimental conditions with one of the robots. In order to overcome limitations of a within-subject design and decrease the impact of a learning effect, the videos presented to each participant in pseudo-random order, but also ensuring that two expressions of the same type were never presented one after another.

Participants watched the video clips whilst seated in a quiet room, completing ratings after each separate clip. They were recorded the whole way through the experiment and at the end of the experiment participants were invited for a 5-10 minute recorded interview, after which they were debriefed. The duration of the experiment did not exceed thirty-five minutes and though participants were informed that they could leave at any time, none decided to do so.

8.2.7 Data Analysis

Cronbach's α was used as a measure of internal agreement between subjects. For the videos showing only the context the α value for the ratings was 0.835, and for the videos showing only the emotional expressions the α value was 0.607. The ratings for the videos showing the combinations of the context and emotional expressions, the α value for the ratings was 0.708. All these α values are acceptable, indicating a good level of internal agreement between all subjects across all the scenarios and respective video conditions.

Mixed measures ANOVA was used to examine the relation between each design parameter and the SAM ratings for the two robots. The same test with different factors was used to evaluate the potential influence of context consistency.

8.3 Results

We compared the recognition results for the two types of robots used in the experimental study. In addition, we conducted several tests of two factor mixed measures ANOVA to analyse an influence of different design parameters on the perception of robot's valence, arousal and dominance. We also analysed the influence of both between- and within-subject factors on the perceived level of a robot's intention to continue its job.

8.3.1 Correctness and Consistency of Recognition

In this section, we present the recognition results for the expressions presented by both robots within an appropriate situational context.

The tabular presentation of Accuracy, Recall and F-score values for each emotional expression of the two robots are given in the Table 8.2.

Overall, the Accuracy of recognition was high for all the emotions in both robots. For the robot of higher expressivity E4, Accuracy was ranging between the lowest 77% value for *surprise* and the highest 95% value for *happiness*. For the robot of lower expressivity Sphero, Accuracy was ranging between the lowest 0.80% value for *anger* and the highest 87% value for *happiness*. For both robots,the Accuracy values were quite similar for each presented emotional expression and all the values were higher than the chance level, as shown in the Figure 8-2.

Other measures, such as Recall and F-scores were more varied compared to Accuracy. The highest Recall rates were detected for *happiness* and were as high as 94%

	Accuracy		Recall		F-score	
	E4	Sphero	E4	Sphero	E4	Sphero
fear	0.88	0.85	0.56	0.80	0.61	0.68
anger	0.82	0.80	0.51	0.05	0.66	0.09
happiness	0.95	0.87	0.94	0.53	0.85	0.61
sadness	0.82	0.81	0.12	0.15	0.18	0.24
surprise	0.77	0.86	0.85	0.50	0.55	0.59

Table 8.2: *The tabular presentation of Accuracy, Recall and F-score values for each presented robot emotional expression in two robots, E4 and Sphero. These data are plotted in Figure 8-2 and 8-3.*

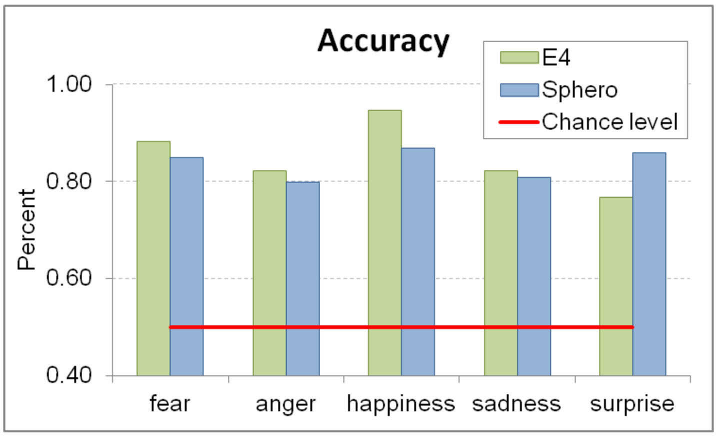


Figure 8-2: *Accuracy of recognition for the five presented emotional expressions in the E4 and Sphero robots.*

for the E4 robot and 53% for Sphero. Another high value of Recall was detected for *fear* and was as high as 56% for E4 and 80% for the Sphero robot. High Recall values showed the ability of participants to correctly recognize these two emotions presented to them through emotional expressions of the robot. The lowest recall rate was detected for *sadness* in case of the E4 robot and was as low as 12%. In case of the Sphero robot the Recall value for *sadness* was very similar - 15%. The lowest Recall in the case of Sphero, however, was detected for the emotional expression of *anger* and was as low as 5%.

The combination of Precision and Recall are another important measure that characterizes how correctly participants were recognizing emotional expressions of the robot presented to them. The combination of these two values, calculated as F-score, are presented in the Figure 8-3, showing that the values were very similar between two robots for the emotional expressions of *fear, happiness, sadness* and *surprise*. Also, for both robot the F-score was very low for the expression of *sadness*. However, there was a big difference between the F-scores calculated for the expression of *anger*: it was as high as 66% in the case of E4 robot with higher expressivity and as low as 9% for the Sphero robot with lower expressivity.

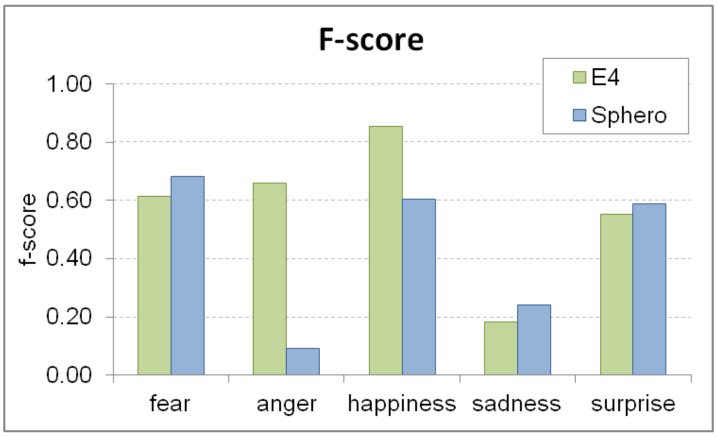


Figure 8-3: *F-scores for the five presented emotional expressions in the E4 and Sphero robots.*

The differences in F-scores were directly related to the differences in recognition rates, as presented in Figure 8-4. Overall, the recognition rates of the expressions of *fear, happiness* and *surprise* were all higher than a chance level. The recognition of the emotional expression of *sadness* was very low for both the E4 robot of higher expressivity and for the Sphero robot of lower expressivity.

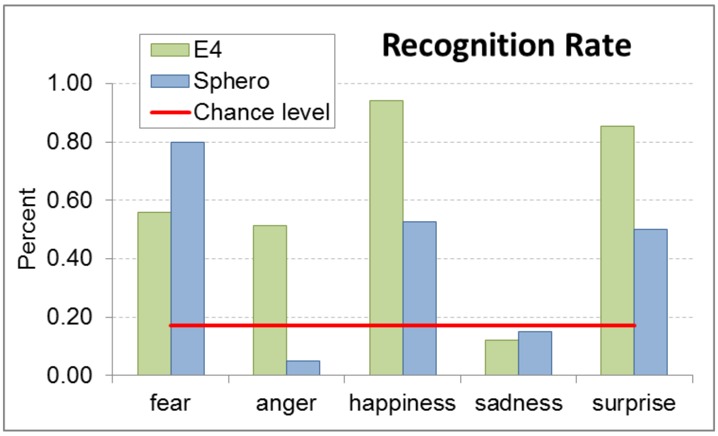


Figure 8-4: *Recognition rates for the five presented emotional expressions in the E4 and Sphero robots.*

The emotional expression of *anger* was the only one which was different for two robots: the recognition rate in the case of E4 robot was as high as 51% and in the case of Sphero robot it was only 5%, which was lower than a chance level.

8.3.2 Perceived Emotional Dimensions

In this section we describe both the commonalities and the differences of the effect of earlier mentioned between- and within-subject factors on the perception of robot's valence, arousal and dominance. As discussed previously, a relation between different design parameters and values of perceived valence, arousal and dominance provide insights of why one emotions are more often or less often misclassified as others. In this section we present how different is this relation for the robots of different expressivity.

Overall, there were no significant differences between the two robots in terms of perceived valence, arousal or dominance for emotional expressions of *fear, anger, happiness* and *surprise*, as presented in Figure 8-5.

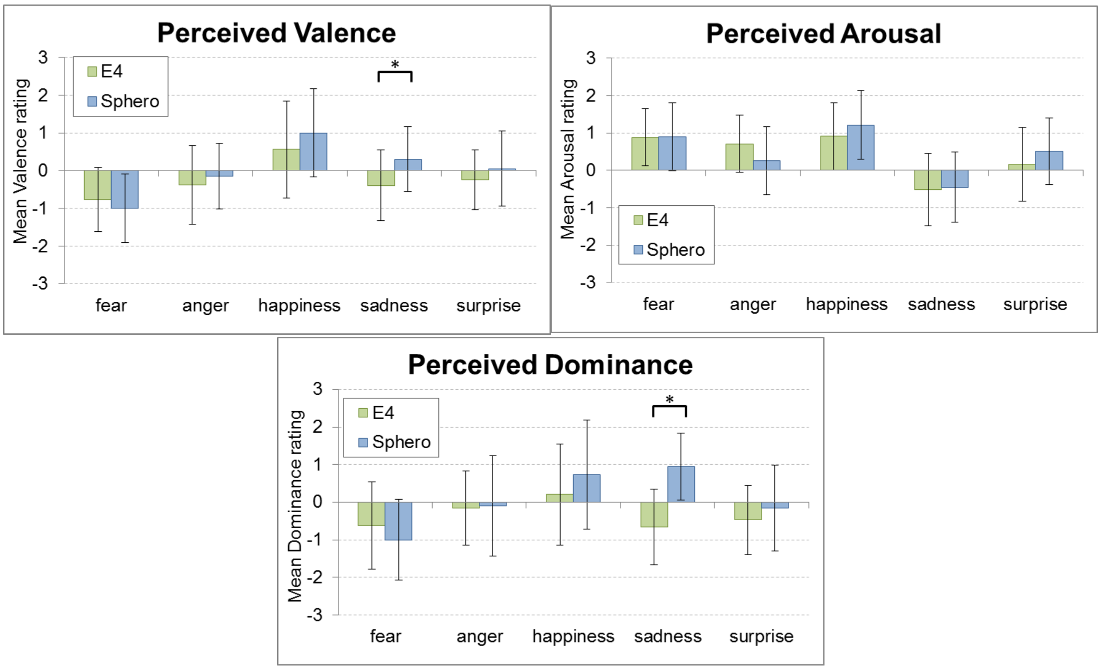


Figure 8-5: *Perceived vaeence, arousal and dominance for the five presented emotional expressions in the E4 and Sphero robots. Symbol * represents p < 0.05.*

Perceived valence and perceived dominance were both significantly different for the emotional expression of *sadness*, with the significantly higher values in the case of the Sphero robot. However, as it was discussed in the previous section, the recognition rate of *sadness* for both robots was lower than a chance level, so it is possible to say that for the recognized emotions the perceived valence, arousal and dominance was not significantly different.

In order to understand in more detail how the specific design parameters influenced the observers' emotional perception, we performed analysis on the impact of design parameters on the perceived valence, arousal and dominance.

The overview of all the ANOVA tests results showing the effect of different DPs on a perceived valence, arousal and dominance are shown in the Table 8.3.

We found a significant difference in the SAM ratings of the effect of *Approach* and *Avoidance* design parameters. The first column of the left part of the Figure 8-6 shows that the mean valence rating for the avoidance behaviours for both robots (mean=-0.43, 95% CI=[-0.54, -0.31]) was lower than approach behaviours (mean=-0.22, CI%=[-0.36, 0.08]). The mean dominance rating for avoidance behaviours (mean=-0.49, 95% CI=[-

	SHAPE			QUALITY								
	2 (Robots: Sphero, E4) x 3 (DPs: Approach, Avoidance, Neutral) ANOVA			**2 (Robots: Sphero, E4) x 2 (DPs: High Energy, Low Energy) ANOVA**			**2 (Robots: Sphero, E4) x 2 (DPs: High Intensity, Low Intensity) ANOVA**			**2 (Robots: Sphero, E4) x 3 (DPs: High, Medium, Low Frequency) ANOVA**		
	DPs	**DPs xRobots**	**Robots**	**DPs**	**DPs xRobots**	**Robots**	**DPs**	**DPs xRobots**	**Robots**	**DPs**	**DPs xRobots**	**Robots**
Perceiv. Valence	$F_{1.8,573.3}$ =15.14, **p<0.001**	$F_{1.8,573.3}$ =0.54, p=0.566	$F_{1,315}$ =1.69, p=0.195	$F_{1,157}$ =51.02, **p<0.001**	$F_{1,157}$ =2.84, p=0.094	$F_{1,157}$ =0.99, p=0.320	$F_{1,477}$ =1.48, p=0.224	$F_{1,477}$ =2.79, p=0.096	$F_{1,477}$ =1.36, p=0.244	$F_{1.83,289.5}$ =15.84, **p<0.001**	$F_{1.83,289.5}$ =8.71, **p<0.001**	$F_{1,158}$ =0.14, p=0.705
Perceiv. Arousal	$F_{1.9,602.3}$ =191.33, **p<0.001**	$F_{1.9,602.3}$ =38.54, **p<0.001**	$F_{1,314}$ =0.04, p=0.835	$F_{1,157}$ =93.57, **p<0.001**	$F_{1,157}$ =0.01, p=0.949	$F_{1,157}$ =3.79, p=0.053	$F_{1,475}$ =261.15, **p<0.001**	$F_{1,475}$ =35.01, **p<0.001**	$F_{1,475}$ =0.44, p=0.507	$F_{2,314}$ =56.73, **p<0.001**	$F_{2,314}$ =4.94, **p=0.008**	$F_{1,157}$ =3.93, **p=0.049**
Perceiv. Dominance	$F_{2,614}$ =20.14, **p<0.001**	$F_{2,614}$ =5.63, **p<0.005**	$F_{1,307}$ =006, p=0.810	$F_{1,156}$ =31.60, **p<0.001**	$F_{1,156}$ =5.69, **p<0.05**	$F_{1,156}$ =0.05, p=0.831	$F_{1,467}$ =0.02, p=0.877	$F_{1,467}$ =12.97, **p<0.001**	$F_{1,467}$ =0.13, p=0.716	$F_{2,310}$ =1.66, p=0.193	$F_{2,310}$ =6.01, **p<0.005**	$F_{1,155}$ =1.89, p=0.171
Perceiv. Intention	$F_{2,636}$ =5.11, **p=0.006**	$F_{2,636}$ =2.50, p=0.083	$F_{1,318}$ =0.57, p=0.452	$F_{1,157}$ =9.15, **p<0.005**	$F_{1,157}$ =6.71, **p<0.05**	$F_{1,157}$ =0.08, p=0.781	$F_{1,477}$ =6.35, **p<0.05**	$F_{1,477}$ =0.16, p=0.693	$F_{1,477}$ =4.94, **p<0.05**	$F_{2,314}$ =2.19, p=0.114	$F_{2,314}$ =0.69, p=0.505	$F_{1,157}$ =5.12, **p=0.025**

Table 8.3: *ANOVA results, showing the effect of different design parameters (DPs) on perceived Valence, Arousal and Dominance, using the more expressive E4 and less expressive Sphero robots.*

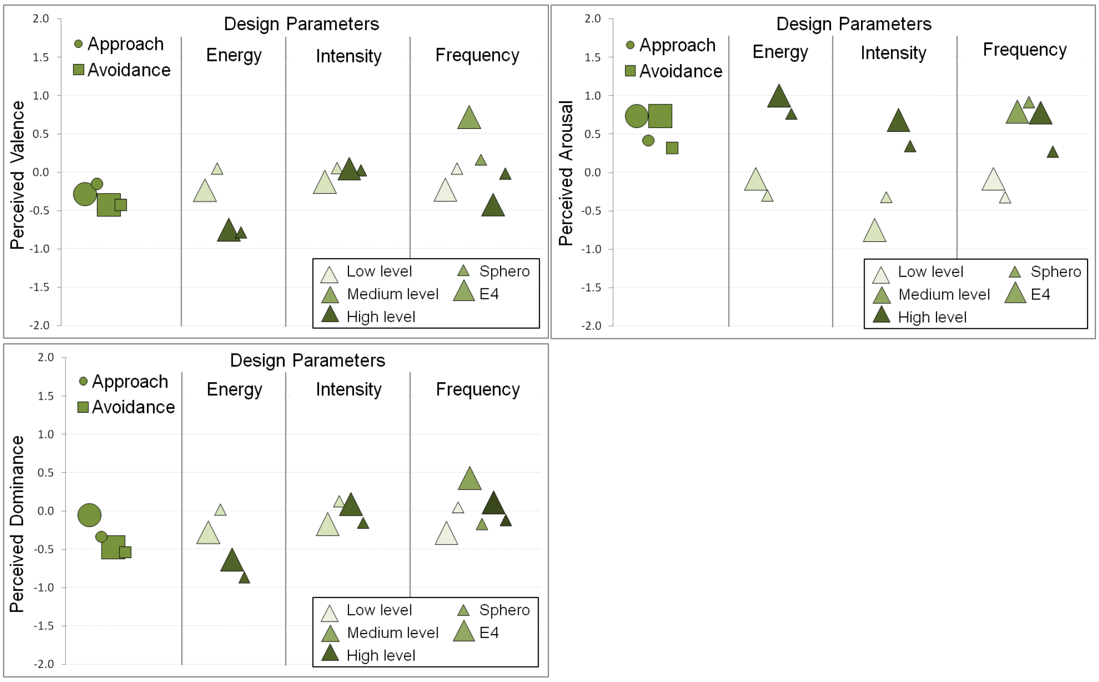


Figure 8-6: *Plot of the mean values of perceived Valence (top left), Arousal (top right) and Dominance (bottom left) for the expressions with implemented parameters of approach-avoidance, energy, intensity and frequency, using the more expressive E4 and less expressive Sphero robots.*

0.61, -0.37]) was lower than for approach (mean=-0.20, 95% CI=[-0.33, -0.07]), as shown in the first column of the right part of the Figure 8-6. The effect of interaction between a robot and DP was significant for the perception of arousal and dominance, although the interaction only influenced the observers' ratings when the design factor changed from neutral to not neutral. While changing from approach to avoidance, the interaction effect did not differ significantly.

We found a significant difference in the effect of high and low *Energy* DP on valence, arousal and dominance ratings. The mean valence rating for high-energy behaviours (mean=-0.77, 95% CI=[-0.93, -0.60]) was lower than that of a low energy expression (mean=-0.09, 95% CI=[-0.24, 0.05]). The mean score of arousal for the expression of a low energy (mean=-0.19, 95% CI=[-0.37, -0.02]) was significantly lower than that of a high energy expression (mean=0.88, 95% CI=[0.74, 1.02]). The mean score of dominance for the expression of a low energy (mean=-0.13, 95% CI=[-0.31, 0.05]) was significantly higher than that of a high energy expression (mean=-0.75, 95% CI=[-0.92, -0.58]). The mean scores are presented in the second columns of each plot in the Figure 8-6. The effect of interaction between a robot and DPs was significant for the perception of dominance: for the more expressive E4 robot the effect of a high-energy DP was stronger than for the less expressive Sphero.

We found a significant difference in the effect of high and low *Intensity* DP on ratings of arousal. The mean arousal rating for the behaviours of low intensity (averaged for both robots; mean=-0.54, 95% CI=[-0.64, -0.43]) was significantly lower ($p<0.001$) than for those with high intensity (mean=0.51, 95% CI=[0.42, 0.61]). The interaction between Robot and DP was significant for dominance: for E4 robot, the mean rating of valence for low-intensity expressions (mean=-0.13) was lower than that of high-intensity expressions (mean=0.05) although the difference between these two values was not significant. For Sphero, mean valence rating for low-intensity (mean=0.06) was higher than that of high-intensity behaviours (mean=0.03) although this difference was either not significant (see third columns of each plot in Figure 8-6.

Finally, we found a main effect for the *Frequency* DP on ratings of valence and arousal. Expressive behaviours of medium frequency received the highest valence ratings (mean=0.44, 95% CI=[0.23,0.65]) comparing to those of low (mean=-0.09, 95% CI=[-0.23,0.05]) and high frequency (mean=-0.22, 95% CI=[-0.40, -0.04]). Medium frequency behaviours also received the highest arousal ratings (mean=0.85, 95% CI=[0.69, 1.01]) comparing to those of low- (mean=-0.20, 95% CI=[-0.38, -0.03]) and high-frequency (mean=0.53, 95% CI=[0.39, 0.66]) (see last columns of each plot in Figure 8-6.

With respect to *Consistency*, our data suggest that valence, arousal and dominance of a robot's expression are not strongly influenced by positive and negative events in the robot's operational context. However, we found positive context to significantly ($p<0.001$) increase the mean ratings of both valence (mean=0.58, 95% CI=[0.41, 0.75]) and dominance (mean=0.93, 95% CI=[0.75, 1.10]) when compared to negative contexts. Additionally, the context of a negative arousal significantly ($p<0.005$) decreased the mean arousal rating (mean=-0.42, 95% CI=[-0.60, -0.25]).

8.3.3 Value of Emotional Expressions

We treated the value of emotional expressions primarily in terms of their ability to support inferences about a robot's intentions to continue cleaning the room, and the successfulness of its cleaning actions.

Observer Judgement of Robot Intentions

In order to asses how different design parameters influence participants' judgments of a robot's intentions and how these differ between two robots of different expressivity levels, we conducted several ANOVA tests. The findings reveal that the ratings of robot intention vary significantly depending on its expressive movements.

Row four of Table 8.3 presents ANOVA results for the four types of DP on perceived Intention. We only discuss contrasts that reached statistical significance.

We found a significant difference main effect of *Approach* and *Avoidance* on judgement of robot intention. The mean score of intention for the approach expression (mean

= 2.81, 95% CI=[2.67, 2.95]) was significantly higher than either neutral (mean=2.54, 95% CI=[2.40, 2.68]) or avoidance expression (mean=2.59, 95% CI=[2.46, 2.72]). We also found that ratings of intention for differed by *Energy* levels. The mean score of intention for the expression of a low energy (mean=2.81, 95% CI=[2.60, 3.01]) was higher than that of a high energy expression (mean=2.46, 95% CI=[2.28, 2.63]). Although the size of effect is small in both cases, our participants were highly consistent in their ratings on these two measures so confidence in these results is high. The main effect of type of robot did not reach significance for Energy or Approach/Avoidance, but robot type did interact with the Energy DP.

There was a main effect of *Intensity* for judgements of robot intention, with a mean score for low-intensity expressions (mean=2.63, 95% CI=[2.52, 2.75]) significantly lower than that for high-intensity expressions (mean=2.82, 95% CI=[2.71, 2.92]). In this case, scores also varied by type of robot, with both high- and low-intensity behaviours of Sphero rated higher overall than their equivalents for E4.

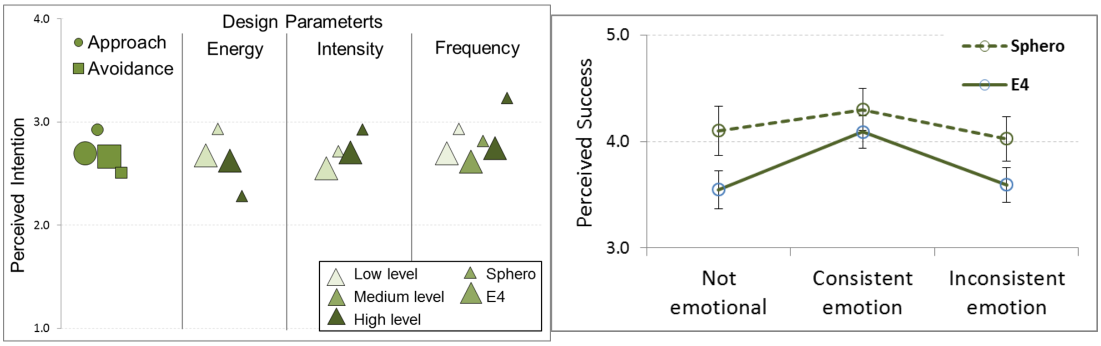


Figure 8-7: *Left: Plot of the mean values of perceived robot's Intention and standard errors for the expressions of Low, Medium and High Frequency, using the more expressive E4 and less expressive Sphero robots. Right: Plot of the mean values of Success and standard errors for robot expressing emotion consistently, inconsistently and not expressing them, using the E4 and Sphero robots. Based on videos where task was completed successfully.*

Observer Judgement of Robot Task Success

Judgement of task success differs from robot intention, as it depends on the interplay between changes in the task environment (its operational context) and the expressive behaviour of the robot. We assume that a person would jointly assess the robot's behaviour and its operational context to decide whether or not its task was completed successfully. If behavioural and operational context both suggest a positive outcome, they are consistent and thus should present a clear signal of success. Similarly, if both are negative, they should clearly signal failure. This is why, in order to assess participants' judgments on robot task success, we use a *consistency of emotion* factor to analyse the data using ANOVA test. The findings reveal that consistent emotional expressiveness increases the rating of a task success and it is significantly different from the cases when a robot completing the task is inconsistently expressive.

A two- (E4 vs. Sphero) x three- (Not emotional, Consistent emotion, Inconsistent emotion) mixed measures ANOVA was used to analyse the influence of expressive behaviour on judgements of task success. In this chapter, we limit our analysis to video clips that objectively show that the block-moving task was in fact completed successfully (see Figure 8-7 Right). The mean rating of success was significantly different for each robot ($F(1.76, 182.98)=3.67$, $p=0.03$, observed power=0.63). Post-hoc tests revealed that observers judge successfulness significantly higher ($p<0.05$) for robots with context-consistent emotional expressions (mean=4.20, 95% CI=[3.95, 4.44]) than for neutral (mean=3.82, 95% CI=[3.54, 4.11]) or context-inconsistent expressions (mean=3.81, 95% CI=[3.54, 4.07]). The difference between two types of robots ($F(1, 104)=4.29$, $p=0.04$) does not interact with this result.

8.4 Discussion

This chapter has reported the implementation of the five basic emotions as robot expressive behaviours in two forms of robot, based on a design scheme for expressing and interpreting emotional body language. The use of two very different robots was intended illustrate the general utility of the design scheme, accompanied by empirical data on human interpretation of the emotional content of these expressive behaviours. Our findings partially support the first hypothesis:

H1. Perceptions of emotionally expressive movements do not vary as a function of the degree of a non-humanoid robot's expressivity.

We found that some design parameters, such as high energy level or avoidance, have a similar influence on observer perceptions of valence, arousal and dominance for both forms of robot i.e. regardless of robot expressivity. These results are consistent with the findings of [166], who showed that (a) high speed of tail movements increased perceived arousal of a robot, and (b) low tail height decreased perceived valence. The latter could be mapped to the *Reduce Yourself* parameter of the *Avoidance* DP group.

Our findings also suggest that some parameters, e.g. approach, high and low intensity or medium and high frequency of movements when implemented in robots of different expressivity level, exert a similar influence on perceptions of a subset of emotional dimensions. For example, high frequency consistently increased ratings of arousal for both types of robots, although its influence on valence differed by robot type. Table 8.4 presents all the similarities between a more expressive and a less expressive robot revealed by our study. These findings partially support our first hypothesis.

However, our study also suggests that there are some significant differences in how some parameters influence perceptions of emotion in robot as a function of expressivity, contrary to our expectations:

Group of design parameters	Perceived Valence	Perceived Arousal	Perceived Dominance
Approach	$\downarrow$ " $-$ "	$\uparrow$ " $+$ "	
Avoidance	$\downarrow$ " $-$ "	$\uparrow$ " $+$ "	$\downarrow$ " $-$ "
Low intensity		$\downarrow$ " $-$ "	
High intensity		$\uparrow$ " $+$ "	
High energy	$\downarrow$ " $-$ "	$\uparrow$ " $+$ "	$\downarrow$ " $-$ "
Medium frequency		$\uparrow$ " $+$ "	
High frequency		$\uparrow$ " $+$ "	

Table 8.4: *Similarities in parameters' influence on valence, arousal and dominance between a more expressive robot E4 and a less expressive robot Sphero. Arrows $\uparrow$ and $\downarrow$ show whether the parameter increased or decreased a perceived value of valence, arousal and dominance. Signs " $-$ " and " $+$ " show whether the value is negative or positive.*

- Both types of robots showed that avoidance behaviours were rated as low dominance. However, for the low-expressivity robot, the ratings was significantly lower than for the highly expressive robot.
- Only the high-expressivity robot is rated with a lower level of dominance for low-frequency expressive behaviours than for high-frequency expressions. In addition, the value of dominance ratings in this case was positive for the low-expressivity robot but negative for the high-expressivity robot.
- The high intensity DP increased the level of perceived valence for the highly expressive robot and made it positive, while for the low-expressivity robot the level of perceived valence was decreased and negative.

Table 8.5 presents all the differences between a more expressive and a less expressive robot revealed by our study. These findings did not support our first hypothesis. They also add to the current knowledge of the design of emotional expressions in robots, as no previous studies suggested that there could be different consequences of applying expressive movements to different types of robots.

In addition to the current knowledge, the Consistency findings of our study revealed that the context of positive valence specifically has a significant effect on perceived valence and dominance of an expressive robot. With respect to perceived arousal, our findings reveal that the context of a negative arousal decreases it significantly. Other contexts, i.e of a positive or negative dominance, positive arousal or negative valence do not have a significant effect on interpretation of an expressive robot.

In contrast to [141], the results of our study do not provide any evidence that the consistency of context can override the interpretation of emotional expression of a robot. Our findings show that inappropriate emotional context is not different to the neutral context cases in interpretation of valence, arousal, dominance and robot inten-

Group of design parameters	Perceived Valence E4	Perceived Valence Sphero	Perceived Arousal E4	Perceived Arousal Sphero	Perceived Dominance E4	Perceived Dominance Sphero
Approach					NA	↓
Avoidance					↓	⇓
Low intensity	↓ ”-”	↑ ”+”			↓ ”-”	↑ ”+”
High intensity	↑ ”+”	↓ ”-”			↑ ”+”	↓ ”-”
Low frequency	↓ ”-”	NA ”+”	NA	↓	↓ ”-”	NA ”+”
Medium frequency	↑	NA			↑ ”+”	NA ”-”
High frequency	↓	NA	⇑	↑		

Table 8.5: *Differences in parameters' influence on perceived valence, arousal and dominance between a more expressive robot E4 and a less expressive robot Sphero. Arrows* $\uparrow$ *and* $\downarrow$ *show whether the parameter increased or decreased a perceived value of valence, arousal and dominance. Wider arrows* $\Downarrow$ *and* $\Uparrow$ *show a stronger decrease/increase effect. Signs* ”$-$” *and* ”$+$” *show whether the value is negative or positive.*

tion. However, our findings correspond to the results of [141] in the part stating that alignment of robot's action and affective context enhanced the affective interpretation.

H2. An observer's beliefs about the success of a robot's actions varies consistently with the nature of the robot's expressive behaviour.

The findings of the study reveal that consistent emotional expressiveness increases the rating of a task success and it is significantly different from the cases when a robot completing the task is inconsistently expressive, e.g. expressed sadness after successfully completing the task, or not expressive, e.g. just completed the task and did not follow it with any emotional expression. Such a result shows that participants' awareness of a situation they observed improved when robot behaved in a consistently emotional way thus supporting our second hypothesis. Our findings conform to those of [97] and [104] by showing an additional value of expressive robot on a neutral one. However, our study also resulted in additional finding that extends the state-of-the-art of HRI and shows that an inconsistently expressive robot does not create an additional situational understanding in human observers although it does not reduce a situational awareness either.

The ratings of robot intention varied significantly depending on its expressive movements. This means that emotional expressions of a robot can not only communicate emotional signal but also let people draw additional inferences about that robot. These findings support the second hypothesis and they are consistent with [67] who stated people may presume other things about affective agents based on their expressiveness, in addition to how he or she is feeling. However, the study of [67] only made this statement about human agents. Our findings make a first step to generalize this idea to a broader set of agents, including robots.

8.5 Conclusions

We attempt to address a gap in the literature between high-level design guidelines for robotic emotional expression using a body language and the implementation of expressive movements in specific non-humanoid robots. We have presented a refinement of the general design scheme proposed in the Chapter 6. We made this design scheme usable for HRI researchers working with different types of non-humanoid robots in two ways. We presented a new technique for classifying non-humanoid robots based on their expressivity. We also demonstrated representations of five basic emotions of fear, anger, happiness, sadness and surprise as sequence of parameters in accordance with the general design scheme. The results of our validation study show both the similarities and differences in the perception of valence, arousal and dominance after applying the design scheme to non-humanoid robots of different expressivity. The Energy and Approach/Avoidance group of DPs were robust across the two robot forms. However, our data suggest a need for a more considered mechanism for describing combinations of parameters, especially in terms of the frequency and intensity of expressive behaviours. There is also a need to create a more sophisticated statistical model instead of performing a series of ANOVA calculations, thus reducing the risk of Type I errors.

Although we adopted a very simple model for estimating the general expressivity of any robot, it proved adequate for the questions we posed. Simple summative models are attractive from a design viewpoint, since they create opportunities for creating equally expressive robots with rather different form factors. They reflect a crude assumption that interpretations depend only on the total number of available cues - a basic bandwidth argument - rather than their choreography. Further work is required to probe the limits of our main finding: interpretations of robot expressive behaviours are consistent, regardless of salient differences in their expressive possibilities. It is hard to imagine non-humanoid form factors of robots that would differ much more than Sphero and E4 but, as we have consistently argued in this chapter, it is not the way they look, it is the way they move that counts from the viewpoint of the observer. We have deliberately limited our enquiry to basic emotional states. Were a designer to explore sophisticated robot emotional expressions, such as guilt, regret or schadenfreude, a different picture may emerge. However, there are also ethical considerations which have directed our work away from matters such as these.

In the next Chapter we will summarise the work presented in this thesis and discuss it with regards to the four main research questions addressed in the thesis. We will overview the main contributions of this work, reflect upon the aspects related to the limitations of the thesis and finalize by providing an overview of the further work that could be undertaken in the future.

CHAPTER 9

DISCUSSION

In this chapter, we bring together the work that has been reported within this thesis to show how the main findings relate to the four research questions it has addressed. We thus discuss the key contributions of this research to HRI. The chapter will also reflect upon the aspects that are related to the limitations of the thesis, as well as in the broader sense. Finally, we will outline a collection of suggestions of future avenues of research.

9.1 Summary and Discussion with Regards to Research Questions

This thesis has addressed the problem of enabling humans to better understand machines by examining the role of artificial emotions synthesized and expressed by robots in the process of human-robot interaction.

The previous research suggests that people and animals benefit from non-verbal communication and use of emotional expressions that make their otherwise unobservable internal states and intentions interpretable to others around them [3, 168]. The same could also be true for robots, as they need to be able to communicate with people using both verbal and non-verbal artificial signals in order to engage humans in interaction [163]. An artificial analogue of natural emotional expressions could make robots more predictable and acceptable, thus making them more effective team-players.

There is a growing body of HRI research on techniques for expressing artificial emotions in robots [107, 6, 49]. However, this research has several limitations that are addressed in this thesis. First of all, the majority of prior research focuses on techniques for expressing artificial emotions via facial expressions [23, 169, 154]. Although such techniques can directly relate human facial expressions to robot emotions, and the results of this research look promising, such an approach limits itself to experimenting with either humanoid robots or robots with a highly expressive human-like faces. In addition, the interaction between people and robots with expressive faces should happen in close proximity in order for the person to see the robot's face clearly, which is not always possible in real-life situations. In this thesis we address this limitation by investigating techniques for expressing emotions via bodily movements of a robot.

Another limitation of previous HRI research in artificial robotic emotions, which is closely related to the first, is that the majority of prior studies are focused on the humanoid robots [86]. The possible reason for such a focused approach could be the popularity of the NAO humanoid robot[1], which is easily accessible for HRI research groups. However, robots do not always have, or may in fact be hampered by, a humanoid or human-like body. Low and semi-expressive non-humanoid robots can be used more often for home-working tasks (e.g. a robotic vacuum cleaner Roomba), search-and-rescue [17], domestic assistance [184] and other tasks. The design of such robots is intended to match their purpose, e.g. designed to move across disaster zones to find and reach victims, or to be steady and move safely in order to help elderly or disabled people get out of bed and move around. Thus it is not always useful or possible for such robots to have human-like bodies. However, as social agents, it is still useful for non-humanoid robots to be able to generate cues that are capable of expressing aspects of their state that are relevant for social coordination. In the natural world, animals must frequently occupy the same space or otherwise need to coordinate their actions, roles and responsibilities. Research on animal emotion, and in the wider field of affect, have shown that non-verbal displays of emotional state play a critical role in this regard: social communication directly assists in the social coordination of action. In this thesis, we sought to address the limitations of prior work on bodily emotional expression in HRI. We have reported a series of investigations on techniques for generating non-verbal expressions of emotion in non-humanoid robots and analyses of the impact of expressive form on the way people interpret emotionally charged robotic expressions. The generation and interpretation of the emotional content of robotic bodily expression must be understood as steps along the way towards realising the potential benefit of emotional expression in human-robot social coordination. In this thesis we sought to address the limited prior work on bodily emotional expressions. We have reported investigations of techniques for generating and expressing emotions in non-humanoid robots and analysed the impact of the form factor on people's interpretation of emotionally charged robotic bodily expressions. These are necessary steps towards realising the potential of human-robot social coordination.

Another limitation of the prior HRI research is that there is a considerable gap between high-level design guidelines for bodily expression of emotion and the imple-

[1]https://www.aldebaran.com/en/humanoid-robot/nao-robot

mentation of a specific robot with expressive movements. In this thesis, we attempted to address this gap by presenting a new technique for classifying non-humanoid robots based on their expressivity and developing a design scheme, which could be usable for HRI researchers working with different types of non-humanoid robots.

Finally, there is still an open question in HRI research about the value of robot emotions in the interaction between people and robots, and especially in human-robot collaboration. In this thesis, we made an attempt to investigate the effects of robotic emotional bodily expressions on people's attitudes towards a robot and on people's behaviour with a robot in a collaborative environment.

9.1.1 RQ1: Do people perceive robotic bodily expressions as having different emotional meanings, and if so, are people consistent in the meaning they perceive?

We addressed the first research question in Chapter 4, in which we reported two exploratory studies, each designed to test human perception of artificial emotions in robot expressive movements of its body and one facial feature in a simple situational context. We investigated the potential for simple features of robotic embodiment to facilitate dynamic emotional signalling in a manner that allows for emotional interpretation by human observers, first with static poses and then with dynamic expressions. The language used to instruct participants was deliberately intended to avoid leading them to use emotional terminology in evaluating robot behaviours.

The results of the two studies revealed the tendency of people to assign an emotional meaning to the observed robot expressions, given a simple context. Both a qualitative and quantitative analysis of the data collected through the studies showed that the majority of participants interpreted robot expressions in an emotional way. We further wished to understand whether the emotional interpretations were simply due to a general human tendency to anthropomorphise, or if they could be subject to a designer's intent. The differences between emotional and non-emotional interpretations of robot's behaviours were statistically significant for all the presented expressions that were designed to be emotionally charged. Besides, the qualitative thematic analysis revealed that in addition to assigning an emotional interpretation to the robot's expressions, people tend to relate robot emotional state to a predicted future or previous interaction. The majority of participants explained the observed robot emotional state as a consequence of a previous interaction, the rest of the answers distributed between explaining the meaning of the observed emotion as 1) a reason for observed behaviour, 2) a tool for interacting with people and 3) a predecessor of a future interaction. The data imply that in general people perceive robotic bodily expressions as having emotional meanings, even when such a meaning is not deliberately provided. However, when a principled approach to design is taken, emotional interpretations are stronger.

The results of the studies reported in the Chapter 4 also imply that people can consistently recognize the emotional meaning they perceive in observed a robot's bodily expressions. The values of recognition ratio detected through two reported studies exceeded the chance level for each recognized emotion of the robot. The results showed a significant difference between an average recognition ratio for positive emotions, such as *happiness* and *excitement*, and non-positive emotions, such as *surprise, anger* or *sadness*, with a lower recognition ratio for positive emotions. The results also showed a significant difference between an average recognition ratio for the emotions of high arousal, such as *surprise* and *excitement*, and the emotions of lower arousal, such as *sadness* or *anger*, with a higher recognition ratio for high arousal emotions in both cases. Not surprisingly, the participants observing dynamic emotions expressed by a real physical robot had in general a significantly higher level of confidence over those observing emotions from static pictures of the robot.

The results of the reported work demonstrate that even very simple movements of a social robot with up to three DoF can convey emotional meanings, showing promise for designing non-humanoid robots that could serve as socially coordinated members of human-robot teams. In particular, this suggests that when people attribute emotional states to a robot, they typically apply an event-based frame to make sense of the robotic expressions they have seen. This suggests that it is possible to create effective robot collaborators without an expressive human-like face, legs, moveable fingers or wrists. The results of this research provide a reason to believe that, in a context of a joint human-robot activity, it should still be possible for interaction designers to use interface elements such as body movements to increase the expressive power of robots and thus increase a social coordination between human and robot in a human-robot team.

9.1.2 RQ2: Can emotionally charged robotic bodily expressions be designed and generated in a systematic pre-structured manner to evoke a desired emotional interpretation?

The second research question was addressed progressively through the work presented for this thesis, but it is the main concern of Chapter 5, Chapter 6 and Chapter 8.

In Chapter 5 we presented an emotionally-based computational model of action selection to control robot behaviours in HRI scenarios. We have implemented the described model as a proof of concept on the physical robot E4. The robot with an implemented model was able to successfully interact with the environment and was also able both to express its internal emotional state and to change its behaviour dynamically according to the implemented action interruption scheme.

However, the presented model of emotional action selection raises several design-related concerns with regards to the addressed research question, that were further investigated in the later chapters. Specifically, it was not clear how to design the emotional expressions in robots in a systematic pre-structured manner that would be understandable by human observers. Thus, in Chapter 6 we presented a design scheme for modelling emotionally expressive robot body movements with a set of design parameters that enabled the creation of emotionally expressive behaviours. This design scheme was further refined and generalized in the Chapter 8.

In Chapter 6 we proposed a design scheme for expressing and interpreting emotional movements in non-humanoid robots that is based on a behavioural form of approach-avoidance analysed from an observer's point of view and the Labanian theory of movement analysis. The scheme includes two concepts to define emotionally expressive behaviours for robots: Expressive Shape and Expressive Quality. Expressive Shape defines how the overall posture of a robot should change in terms of its physical form, and relates this change to the emotional significance of approach and avoidance in the animal world. In order to define the Shape of emotional robot movements, we linked the emotional expression to a more general 'goal' of the expressive robot of either becoming closer to an observer by moving closer or becoming bigger without moving closer. These two groups of movements although very different by their nature could both cue the idea of approach from the observer's point of view and thus communicate a certain emotional meaning. In contrast, Avoidance is designed by either becoming further away from an observer by moving away or becoming smaller without moving away. The Shape group is associated with ten distinct parameters of body motion, such as *transfer weight forward / backwards* or *attract limbs close to the body.* The design group of expressive Quality captures dynamics of an expressive movement and thus defines the performative characteristics of robot movement, i.e. strength or frequency, grounding the meaning of these characteristics in prior work on signals of affective state in animals and people. It is associated with a further thirteen parameters of motion, such as *strength* or *frequency.* In order to investigate whether robotic bodily expressions designed and generated using the proposed scheme evoke a desired emotional interpretation, we implemented the dynamic expressions of five basic emotions of *fear, anger, happiness, sadness* and *surprise* into a non-humanoid robot E4. We asked people to recognize the implemented expressions.

The results of the study showed that the accuracy of recognition was high for all the emotions, mostly due to a high level of recognition specificity and a high number of true negatives. The values of recognition ratio were also high enough and exceeded the chance level for four recognized emotions of *fear, anger, happiness* and *surprise.* The recognition ratio of *sadness* was below the chance level in this study, which suggest that the static posture may represent sadness better than a dynamic expression. The robot expressions of *anger* and *fear* were sometimes misclassified as *surprise*, while the expression of *surprise* was most often misclassified as *fear* and the expression of *happiness* was sometimes misclassified as *anger*. Such errors suggest that some design parameters do not communicate the full emotional information a specific discrete emotion includes, but rather provide observers with the information useful to better detect one emotional dimension and give less information about another dimension.

In Chapter 8 we presented a refinement of this design scheme in order to generalize it to some extent. We made this design scheme usable for HRI researchers working with different types of non-humanoid robots in two ways. First, we presented a new technique for classifying non-humanoid robots based on their expressivity. Second, we demonstrated representations of five basic emotions of *fear, anger, happiness, sadness* and *surprise* as a sequence of parameters on a time scale in accordance with the generalized design scheme. In addition, we validated a refined design scheme on two robots of different form. The results of the study revealed that the values of recognition accuracy were similarly high, and higher than a chance level, for all the five presented emotional expressions in both robots. The recognition ratio in this study was below a chance level for the emotional expressions of *sadness* in both robots, and for the expression of *anger* for a robot with less design parameters available to program and implement.

The results from this study demonstrate that it is possible to design and generate robotic bodily expressions of the emotions of *fear, anger, happiness* and *surprise* in a systematic pre-structured manner using the design scheme proposed in this work and these emotions not only evoke a desired emotional interpretation, but are also recognized on a better-than-chance level when implemented and expressed by a non-humanoid robot having a sufficient expressive ability.

The results of the reported research provide a reason to believe that it is possible to design and generate in a systematic pre-structured manner both the internal emotional state of a robot and its external expression so that they evoke an emotional interpretations intended by a designer.

9.1.3 RQ3: What factors impact how people interpret the emotionally charged bodily expressions of a robot?

We have addressed the third research question in two chapters, Chapter 7 and Chapter 8. In Chapter 7 we focus on the effect of a situational context on interpreting emotional robot body movements. We presented a detailed analysis of the study where people tried to recognize robotic emotions observing the recording of the robot expressing emotions in either contextual scenarios or in a situation with no additional contextual information. In Chapter 8, in contrast, we focused on the effect of a robotic body form and investigated what influence this factor had on how people perceived and interpreted the bodily expressions of two different robots.

The question of the impact of a context on how people interpret the emotionally charged bodily expressions of a robot is still open as there exist very few studies analysing the role of situational context in the interpretation of robot emotions and in the area of human-robot emotional interaction in general. Specifically, there is very little experimental evidence of what biases human interpretations of robot emotions - emotionally charged expressions or contextual information. In Chapter 7 we attempted to address a gap in the literature and presented a study on interaction between situational context and emotional body language in robotics. In the study, participants were rating the videos, showing a robot expressing five basic emotions in different contexts, in terms of their perception of robot's valence, arousal an dominance and they also guessed the emotion expressed by a robot. In general, the findings of this study supported the hypothesis that an emotional expression overrides the interpretation of a situational context in signalling emotional information. More specifically, the perception of arousal for the expressions of *anger, happiness, sadness* and *surprise* was biased by the bodily expressions of the robot and not by the situational context. The findings also showed that the perception of *anger* dominance was also biased by the robot's bodily expression and not by the context in which this expression was performed. In addition, the analysis revealed that alignment of a robot's emotionally expressive action and a context enhanced the affective interpretation.

Such results suggest that, in a context of a joint human-robot activity, it is possible to use simple emotionally charged movements of a robot to either enhance people's interpretation of a robot's internal status or to provide some additional information that is not obvious from (or may even be contradicting) the situational context. The findings are also useful to provide some specific design recommendations and insights as to how emotional robot expressions may be used practically in both real-world settings and future experimental scenarios. For example, it is likely that a robot acting in a neutral way will induce a perception of negative arousal in observers even when something unexpected, sudden or uncontrolled is happening. In order to change arousal to a positive level, robot should visually react to the changes in the environment. Our findings show that emotional bodily expressions are a good way to react to different stimuli and thus convince observers of a higher level of robot's arousal.

Another major factor to investigate is how the morphology of a robot performing emotional expressions influences how these expressions are interpreted. On the one hand, it is common for non-humanoid robots to vary greatly in terms of the number of embodied degrees of freedom, and the maximum amplitude, velocity and frequency of motions they are able to perform. On the other hand, there exists a gap in the literature between high-level design guidelines for robotic emotional expression using a body language and the implementation of expressive movements into specific non-humanoid robots. In the Chapter 8 we addressed the gap by presenting a new technique for classifying non-humanoid robots based on their expressivity and these grounds focused on the impact of robot body form in interpreting its emotional bodily expressions. In this Chapter, we designed an experimental study, in which participants observed and rated video clips of a robot in action. We used a between-subject design for presenting clips of two different robots - a more expressive non-humanoid robot E4 with several limbs to the first group of participants, and a less expressive abstract robotic ball Sphero to the second group. Within each group, we used a within-subject design for presenting subjects with a sequence of expressive behaviours performed by their respective robot. The results of the study showed both the similarities and differences in the perception of valence, arousal and dominance after applying the design scheme to non-humanoid robots of different expressivity. In terms of similarities, we found that some design parameters, such as high energy level or avoidance, have a similar influence on observer perceptions of valence, arousal and dominance for both forms of robot i.e. regardless of robot expressivity. Other design parameters, e.g. approach, high and low intensity or medium and high frequency of movements when implemented into robots of different expressivity level, exert a similar influence on perceptions of a subset of emotional dimensions. For example, high frequency consistently increased ratings of arousal for both types of robots, although its influence on valence differed by robot type.

The results of this work suggest that in many cases the form factor of a robot does not impact the people's interpretations of robot expressive behaviour, although the HRI designers should be aware of some potential differences. However, further work is required to probe the limits of this finding.

9.1.4 RQ4: What are the effects of robotic emotional bodily expressions on people's attitude towards a robot?

We have addressed the last research question in Chapter 6. Here, we presented a design scheme for expressing artificial emotional states in non-humanoid robots and reported the analysis of the human observers' perception of a robot performing emotionally charged movements according to the presented scheme. Human perception was measured using a part of the Godspeed questionnaire that consists of perceived anthropomorphism, animacy, likeability and perceived intelligence of a robot. Thus we addressed the first part of the research question and investigated the effects of robotic emotional bodily expressions on people's attitudes towards robots. In Chapter **??** we reported an experimental study we conducted where human subjects worked alongside a robot on a collaborative table setting task in a simulated environment. The robot behaviour was either emotionally expressive or not emotionally expressive depending on a test condition. In such a way we addressed the second part of the research question and investigated the effects of robotic emotional bodily expressions on people's behaviour with robots during human-robot collaboration.

The results of the work reported in Chapter 6 demonstrate that people perceive emotionally expressive robots as more anthropomorphic, more animate and even more likeable. Specifically, in terms of Anthropomorphism, emotional robots expressing any of five basic emotions of *fear, anger, happiness, sadness* or *surprise* were perceived as being more natural, more humanlike and more conscious. The same was the case with perceived Animacy of the robots expressing these five emotions, when emotional robots were rated as more organic, lifelike and responsive comparing to non-emotional. In terms of Likeability, emotional robots expressing *fear, happiness, sadness* or *surprise* were perceived as more pleasant and being liked more than non-emotional. The results of this research suggest that, in a context of a joint human-robot activity, emotionally expressive robots will be able to better engage people into interaction. The enhanced attitude towards emotionally expressive robots could create a higher level of empathy between people and robots and thus improve the social coordination between them for the purpose of a better collaboration.

In addition, the results of the study reported in Chapter 6 revealed that robots were perceived as more responsible when they expressed the emotions of *anger* or *surprise*. And surprisingly, emotional robots expressing any of five basic emotions of *fear, anger, happiness, sadness* or *surprise* were perceived as being more intelligent. These results provide the evidence to think that in the context of human-robot teamwork an emotionally expressive robot would be a more preferred team member, trusted more by its human collaborator. Obviously, the functional behaviour of a robot should not contradict this assumption, otherwise the process of a human-robot collaboration would not be efficient.

9.2 Summary of the Main Contributions

Overall, this thesis has presented a dense volume of information and data regarding six experimental studies designed to gain deeper insights into the use of artificial emotions during HRI and factors that impact how emotional expressions of robots are perceived by people. The primary original contributions of this work are summarised as follows:

- **The development of a new scheme for designing emotionally expressive body movements in robots of different body forms**. We proposed a computational model for emotionally-based robot control and the design scheme for creating robot emotional expressions based on the previous research on human body language and robot expressive movements. In order to generalize the scheme for different types of non-humanoid robot forms, we explored the concept of a robot expressivity. The design scheme was validated on two different types of non-humanoid robots.

- **Original findings on the role of the context as a factor that may impact people's interpretations of the emotionally charged bodily expressions**

of a robot. The data collected during the performed experimental study showed that the interpretation of robot emotional expressions designed according to the proposed scheme override the interpretation of a situational context.

- **Original findings on the effects robotic emotional bodily expressions have on people's attitudes towards a robot.** The data collected during the performed experimental studies showed that people's judgements on emotionally expressive robots are significantly higher on the measurements of four key concepts in HRI: robot anthropomorphism, animacy, likeability and perceived intelligence.

9.3 Limitations of Studies and Suggestions for Future Research

This section serves out as an outline of some possible future directions of research that are considered as valuable to further understanding of how robotic emotions may be applied to HRI research.

9.3.1 Validating the Design Scheme on Other Robotic Forms

Part of the research in this thesis has touched upon the fact that different morphologies and embodiments are an important factor that impacts how people perceive and interpret bodily expressions of robotic emotions. We have experimented with two different forms of non-humanoid robots. However, neither of these two robots made use of all the possible design parameters described in our proposed design scheme. As a consequence, none of the two robots used was able to fully employ the potential expressive abilities of the developed design scheme. This may be considered as a limitation of our work and thus provide grounds for possible future research, consistently investigating non-humanoid robots of each level of expressivity.

Moreover, the research in this thesis was specifically focused on non-humanoid robot forms. Although non-humanoid robots vary a lot in their expressive abilities and aesthetics, it is also important to validate the proposed design guidelines on humanoid or human-like robotic forms. In our work, we assumed that it should be easy to transfer emotional expressions from humans to humanoid robots, however, there may be both technical and design limitations that require more research in this area.

9.3.2 Improving the Design Scheme by Weighting the Value of DPs

In our work we adopted a very simple summative model for estimating the general expressivity of any robot, although it proved adequate for the questions we posed.

Summative models are attractive from a design viewpoint, since they create opportunities for creating equally expressive robots with rather different form factors. They reflect a crude assumption that interpretations depend only on the total number of available cues - a basic bandwidth argument - rather than their choreography. However, further work is required to probe the limits of such a model, and this is closely related to the potential design scheme validation on different forms and shapes of non-humanoid robots. It is important to understand whether each design parameter adds the same value to the interpretation of a specific emotional expression or some of the parameters have more weight over others.

9.3.3 Investigating the Value of Emotions in Collaborative HRI Scenarios

The work reported in this thesis focused on human observations of robot actions. Having a coherent design scheme to produce meaningful emotional expressions through robot body movements, it is important to investigate the impact of such expressions on people's behaviour with a robot.

In human-human teamwork, team members routinely monitor their collaborators' attitudes to their individual and joint activity through the interpretation of their emotional signals. As collaborators, it is important for team members to maintain mutual appreciation of attitudes towards the progress of both individual and collective elements of joint work. Dynamic human coordination depends on inferences drawn from evidence about such attitudes during the production of joint work. These inferences combine evidence in the form of events people perceive in the shared space, and in the form of the expressions produced by their collaborators, allowing people to form beliefs about the challenges currently facing collaborators, and about their intended actions. For people, affective expressions are an important part of a successful collaboration. Affective expressions of robots could also aid to a success and efficiency of human-robot collaboration and this may be a fruitful theme for the future research.

9.3.4 Including People's Emotional Reactions into the Loop

The majority of the research in this thesis was focused on how people interpret emotionally expressions performed by robots. However, from an interaction perspective, understanding of social cues and a social context should not be considered as a one-sided process. In human-robot interaction, people not only interpret the emotional signals of others around them but also intuitively signal their emotional state. For robot emotional signals to function effectively in human-robot interactions, it is also necessary to consider the dynamic nature of social interaction and to adapt robot's behaviours to the human's emotional reactions. If such developments were to begin successfully emerging it would paint a bright future for the long-term emotionally enriched communication in real social HRI.

9.3.5 Long-Term Human-Robot Interaction

Establishing and maintaining Long-Term HRI is a very current goal of the field of HRI, and is something that is now beginning to be tackled head on. It is not clear exactly how people will respond to robots, generally, after long periods of time, and this applies to a very large number of different aspects of HRI. As such, it is likely that many findings that have already been reported are likely to require validation and replication with respect to their validity during Long-Term HRI.

This is also true for the use of emotional expressions in robots. However, if emotional expressions indeed can be used in a robot for longer term interactions, a great number of interesting questions emerge from this. For example, use of emotions through long term interactions may also be a way of solving the lack of consistency that people exhibit. It can be argued that an important factor that leads to this inconsistency is that lack of prior experience that can be drawn upon in order to decode the affective meaning that different expressions can have. Through having increased experience with the expressions a robot makes in different situations, it is likely that people will begin to form associations between the expressive features and the perceived affective meanings. Most of this is of course highly speculative, but if such developments were to begin emerging it would paint a very bright future for the use of emotions in real social HRI in the long term.

APPENDIX A

APPENDIX A

The following document presents a documentation for the reported exploratory study. First, it presents an Ethics check list, completed for the study. Next, it presents a briefing script. And finally, it presents a response form provided to the participants to fill in during the study.

UNIVERSITY OF BATH

Department of Computer Science

13-POINT ETHICS CHECK LIST: Robot Reactions Study

1. *Have you prepared a briefing script for volunteers?*
   Yes. See **Appendix A**.

2. *Will the participants be using any non-standard hardware?*
   No. Participants will be observing a custom-build Lego robot.

3. *Is there any intentional deception of the participants?*
   Not attempt will be made to mislead participants in this study.

4. *How will participants voluntarily give consent?*

Participants will consent to take part verbally and demonstrate their consent by filling in a response form on which it will be clearly marked that so doing indicates consent. See **Appendix B**

5. *Will the participants be exposed to any risks greater than those encountered in their normal work life?*
   No.

6. *Are you offering any incentive to the participants?*

No incentive is offered.

7. *Are any of your participants under the age of 16?*

The study is to take place at a public open day and will be open to all visitors, regardless of age. Minors will only be allowed to take part if their parent or guardian is present.

8. *Do any of your participants have an impairment that will limit their understanding or communication?*

All participants will be asked to assert that they understand what the study requires them to do before commencing. If they do not understand, they will be asked to watch other people participating rather than to participate themselves. Questions posed by visitors about the study procedure, robot construction, study purpose or data analysis will be answered as they are raised.

9. *Are you in a position of authority or influence over any of your participants?*

It is possible that visitors will feel that they must comply with requests to take part in the study. The briefing document clearly states that participation in this study is not a condition of their visit to the University of Bath in general, or to the Computer Science demonstrations in particular (See **Appendix A**).

10. *Will the participants be informed that they could withdraw at any time?*

Participants will be informed that they can withdraw from the study at any time. This is clearly indicated on the Response Form (**Appendix B**).

11. *Will the participants be informed of your contact details?*

The supervisor's contact details are included on the Briefing Script (See **Appendix A**).

12. *Will participants be de-briefed?*

A verbal debriefing will be given following the study, stating that the research aims at improving human-robot coordination and teamwork, and participants will be shown summary statistics of responses so far gathered.

13. *Will the data collected from the participants be stored in an anonymous form?*

Personal data will not be retained in this study.

NAME: _____Jekaterina Novikova__________

SUPERVISOR (*IF APPLICABLE):* ____Dr Leon Watts______

SECOND READER (IF APPLICABLE): ___ n/a ______

PROJECT TITLE: ____ Guess the Robot Reaction ______

DATE: _____ 14th of September 2013________

Appendix A: Robot Reactions Study Briefing Script

Imagine you are watching a small robot exploring a room. It notices something, stops and reacts. What does its reaction mean?

We are investigating how people interpret robot behaviours. Robots can move around from place to place and move their bodies to inspect things. It is important to design robots so that people can understand what they are doing.

First, we would like you to watch a simple Lego robot reacts to something and to describe the robot's reaction in your own words. Then we'll show you the same robot's reactions one more time and ask you to choose the best description from a list we have thought up.

Afterwards, we would like you to choose the most likely 'what happens next' from another list.

We shall not use your name in our analysis or in any of our reports. This is an ***exploratory study:*** that means there are no right or wrong answers. We shall use the things you write and the choices you have made to help guide our research on robot behaviour. You are not required to participate in this study in order to see the Computer Science demonstrations today, or for any other reason connected with your visit to the University of Bath.

If you are happy to do the things described above and would like to take part in our study, please collect a form in EB0.8 and wait to be shown what to do next.

If you have any questions about this research,
please contact Jekaterina Novikova (j.novikova@bath.ac.uk) or my supervisor Dr Leon Watts by email: l.watts@bath.ac.uk

Appendix B: Robot Reactions Study Response Form

Completing this form indicates that you have read the Briefing Script and on that basis you consent to taking part in this study. You are free to stop at any time, should you change your mind.

Your age: ……………………………………………………

Your gender: Female ☐ Male ☐

Imagine you are watching a small robot exploring a room. It notices something, stops and reacts. What does its reaction mean?

Please write in your own words how you would describe each of the robot's reactions:

REACTION 1	The robot was:
REACTION 2	The robot was:
REACTION 3	The robot was:
REACTION 4	The robot was:
REACTION 5	The robot was:

Thank you for taking part!

If you have any questions about this research, please contact Jekaterina Novikova (j.novikova@bath.ac.uk) or my supervisor Dr Leon Watts by email l.watts@bath.ac.uk

APPENDIX B

APPENDIX B

The following document presents a briefing script for the reported study.

Human-Robot Interaction Study Briefing Script

We are investigating how people interpret robot behaviours. Robots can move around from place to place and move their bodies to inspect things. It is important to design robots so that people can understand what they are doing.

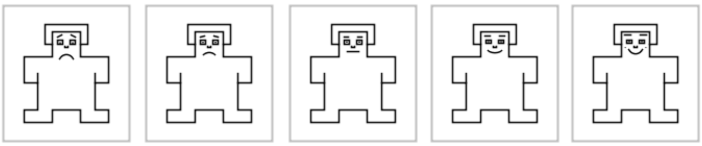
We shall not use your name in our analysis or in any of our reports. This is an exploratory study: that means there are no right or wrong answers. We shall use the things you write and the choices you have made to help guide our research on robot behaviour. All the data provided by you will be used for scientific purposes only and will be treated confidentially. Any identifying information of your identity will be removed.

Participation in the project is voluntary, and we highly appreciate your participation.

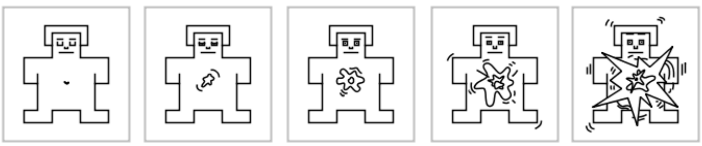
First, we would like you to fill in a questionnaire.

Afterwards, we would like you to watch twenty three short videos 5-10 sec each. After each video please select the best answers from the list we have prepared.

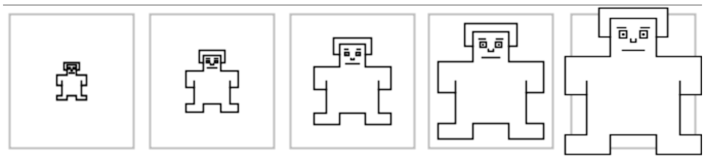
Explanations:



This scale describes the positive or negative feeling caused by a situation, an object or an event. E.g. anger and anxiety are supposed to be negative, joy is supposed to be positive.



This scale describes the perceived vigilance as a physiological and psychological condition. The range reaches from doziness or boredom to excitation.



This scale describes how much a robot feels in control of a situation. A small figure means that the it has no power to handle the situation.

Imagine the robot's job is to clean a room. Its current task is to move a green block to an allocated place.

If you have any questions about this research, please contact Jekaterina Novikova (j.novikova@bath.ac.uk)

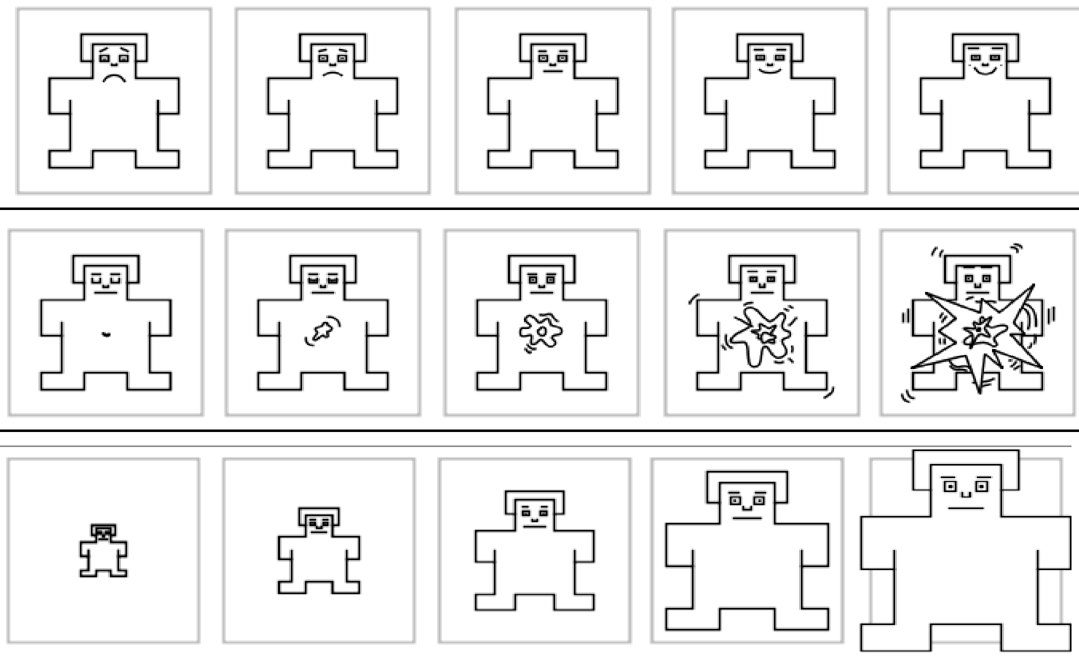
APPENDIX C

APPENDIX C

The following document presents a questionnaire provided to the participants of the reported study.

Video clip No.

1 Please select the image in each of three sets that best represents the robot in this video:



2 Please select the most suitable word to describe the robot in this video:

- ○ afraid
- ○ angry
- ○ happy
- ○ sad
- ○ surprised
- ○ not emotional
- ○ other

3 Please rate your impression of the robot on these scales:

Fake	○	○	○	○	○	Natural
Machinelike	○	○	○	○	○	Humanlike
Unconscious	○	○	○	○	○	Conscious
Mechanical	○	○	○	○	○	Organic
Artificial	○	○	○	○	○	Lifelike
Apathetic	○	○	○	○	○	Responsive
Dislike	○	○	○	○	○	Like
Unpleasant	○	○	○	○	○	Pleasant
Irresponsible	○	○	○	○	○	Responsible
Unintelligent	○	○	○	○	○	Intelligent
Foolish	○	○	○	○	○	Sensible

4 Do you think the robot's task was completed successfully?

Definitely No	○	○	○	○	○	Definitely Yes

5 Do you think the robot is going to continue its job?

Definitely No	○	○	○	○	○	Definitely Yes

BIBLIOGRAPHY

[1] It's not the way you look, it's how you move: Validating a general scheme for robot affective behaviour. In *Human-Computer Interaction – INTERACT 2015*, volume 9298 of *Lecture Notes in Computer Science*, pages 239–258. Springer International Publishing, 2015.

[2] Kenji Amaya, Armin Bruderlin, and Tom Calvert. Emotion from motion. In *Proceedings of the conference on Graphics interface'96*, pages 222–229. Canadian Information Processing Society, 1996.

[3] Michael Argyle. *Bodily communication.* London: Methuen, 1988.

[4] Magda B. Arnold. *Emotion and Personality.* Columbia University Press, 1960.

[5] Hillel Aviezer, Yaacov Trope, and Alexander Todorov. Body cues, not facial expressions, discriminate between intense positive and negative emotions. *Science*, 338(6111):1225–1229, 2012. American Association for the Advancement of Science.

[6] Ruth Aylett, Wolmet Barendregt, Ginevra Castellano, Arvid Kappas, Nuno Menezes, and Ana Paiva. An Embodied Empathic Tutor. In *Papers from the 2014 AAAI Fall Symposium*, pages 39–41. Association for the Advancement of Artificial Intelligence, 2014.

[7] Rainer Banse and Klaus R Scherer. Acoustic profiles in vocal emotion expression. *Journal of personality and social psychology*, 70(3):614–636, 1996. American Psychological Association.

[8] Simon Baron-Cohen. *Theory of mind and face-processing: How do they interact in development and psychopathology?* John Wiley & Sons, 1995.

[9] Lisa Feldman Barrett and James A Russell. The structure of current affect controversies and emerging consensus. *Current Directions in Psychological Science*, 8(1):10–14, 1999. SAGE Publications.

[10] C Christoph Bartneck. *eMuu: an embodied emotional character for the ambient intelligent home*. PhD thesis, Technische Universiteit Eindhoven, 2002.

[11] Christoph Bartneck, Takayuki Kanda, Omar Mubin, and Abdullah Al Mahmud. Does the design of a robot influence its animacy and perceived intelligence? *International Journal of Social Robotics*, 1(2):195–204, 2009. Springer.

[12] Christoph Bartneck, Dana Kulić, Elizabeth Croft, and Susana Zoghbi. Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International journal of social robotics*, 1(1):71–81, 2009. Springer.

[13] Joseph Bates et al. The role of emotion in believable agents. *Communications of the ACM*, 37(7):122–125, 1994. ACM.

[14] Aryel Beck, Antoine Hiolle, Alexandre Mazel, and Lola Cañamero. Interpretation of emotional body language displayed by robots. In *Proceedings of the 3rd international workshop on Affective interaction in natural environments*, pages 37–42. ACM, 2010.

[15] Aryel Beck, Brett Stevens, Kim A Bard, and Lola Cañamero. Emotional body language displayed by artificial agents. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 2(1):2:1–2:29, 2012. ACM.

[16] Christian Becker-Asano. *WASABI: Affect simulation for agents with believable interactivity*, volume 319. IOS Press, 2008.

[17] Cindy L Bethel and Robin R Adviser-Murphy. *Robots without faces: non-verbal social human-robot interaction*. PhD thesis, University of South Florida, 2009.

[18] Timothy W Bickmore and Rosalind W Picard. Towards caring machines. In *CHI'04 extended abstracts on Human factors in computing systems*, pages 1489–1492. ACM, 2004.

[19] James Borg. *Body Language: 7 Easy Lessons to Master the Silent Language*. Pearson Education Inc. Publishing as FT Press, 2009.

[20] Margaret M Bradley and Peter J Lang. Measuring emotion: the self-assessment manikin and the semantic differential. *Journal of behavior therapy and experimental psychiatry*, 25(1):49–59, 1994. Elsevier.

[21] Virginia Braun and Victoria Clarke. Using thematic analysis in psychology. *Qualitative research in psychology*, 3(2):77–101, 2006. Taylor & Francis.

[22] Scott Brave and Clifford Nass. The human-computer interaction handbook. chapter Emotion in Human-computer Interaction, pages 81–96. L. Erlbaum Associates Inc., Hillsdale, NJ, USA, 2003.

[23] Cynthia Breazeal. Emotion and sociable humanoid robots. *International Journal of Human-Computer Studies*, 59(1):119–155, 2003. Elsevier.

[24] Cynthia Breazeal. *Designing Sociable Robots*. MIT Press, Cambridge, MA, USA, 2004.

[25] Inge Bretherton and Marjorie Beeghly. Talking about internal states: The acquisition of an explicit theory of mind. *Developmental psychology*, 18(6):906, 1982. American Psychological Association.

[26] Joost Broekens. In Defense of Dominance: PAD Usage in Computational Representations of Affect. *International Journal of Synthetic Emotions (IJSE)*, 3(1):33–42, 2012. IGI Global.

[27] Joost Broekens and Willem-Paul Brinkman. AffectButton: a method for reliable and valid affective self-report. *International Journal of Human-Computer Studies*, 71(6):641–667, 2013. Elsevier.

[28] Joost Broekens, Anne Pronker, and Marian Neuteboom. Real time labeling of affect in music using the affectbutton. In *Proceedings of the 3rd international workshop on Affective interaction in natural environments*, pages 21–26. ACM, 2010.

[29] Rodney Brooks. A robust layered control system for a mobile robot. *Robotics and Automation, IEEE Journal of*, 2(1):14–23, 1986. IEEE.

[30] Joanna Bryson and Kristinn R Thórisson. Dragons, bats and evil knights: A three-layer design approach to character-based creative play. *Virtual Reality*, 5(2):57–71, 2000. Springer.

[31] Joanna J Bryson. The behavior-oriented design of modular agent intelligence. In *Agent technologies, infrastructures, tools, and applications for e-Services*, pages 61–76. Springer, 2003.

[32] Joanna J Bryson, Tristan J Caulfield, and Jan Drugowitsch. Integrating lifelike action selection into cycle-based agent simulation environments. *Proceedings of Agent 2005: Generative Social Processes, Models, and Mechanisms*, 2005. Chicago: Argonne National Laboratory.

[33] Joanna J Bryson and Philip P Kime. Just an artifact: why machines are perceived as moral agents. In *Proceedings of the Twenty-Second international joint conference on Artificial Intelligence-Volume Volume Two*, pages 1641–1646. AAAI Press, 2011.

[34] Joanna J Bryson and Lynn Andrea Stein. Modularity and design in reactive intelligence. In *International Joint Conference on Artificial Intelligence*, volume 17, pages 1115–1120. IJCAI Press, 2001.

[35] Joanna J Bryson and Emmanuel Tanguy. Simplifying the design of human-like behaviour: Emotions as durative dynamic state for action selection. *International Journal of Synthetic Emotions (IJSE)*, 1(1):30–50, 2010. IGI Global.

[36] Lola D Canamero and Jakob Fredslund. How does it feel? emotional interaction with a humanoid lego robot. In *Proc. of American Association for Artificial Intelligence Fall Symposium, FS-00-04*, pages 7–16. AAAI Press, 2000.

[37] Roger A Chadwick, Douglas J Gillan, Dominic Simon, and Skye Pazuchanics. Cognitive analysis methods for control of multiple robots: Robotics on $5 a day. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 48, pages 688–692. SAGE Publications, 2004.

[38] Diane Chi, Monica Costa, Liwei Zhao, and Norman Badler. The emote model for effort and shape. In *Proceedings of the 27th annual conference on Computer graphics and interactive techniques*, pages 173–182. ACM Press/Addison-Wesley Publishing Co., 2000.

[39] Jeffrey F Cohn, Lawrence Ian Reed, Tsuyoshi Moriyama, Jing Xiao, Karen Schmidt, and Zara Ambadar. Multimodal coordination of facial action, head rotation, and eye motion during spontaneous smiles. In *Automatic Face and Gesture Recognition, 2004. Proceedings. Sixth IEEE International Conference on*, pages 129–135. IEEE, 2004.

[40] Géraldine Coppin and David Sander. Contemporary theories and concepts in the psychology of emotions. *Emotion-Oriented Systems*, pages 1–31. Wiley Online Library.

[41] Mark Coulson. Attributing emotion to static body postures: Recognition accuracy, confusions, and viewpoint dependence. *Journal of nonverbal behavior*, 28(2):117–139, 2004. Springer.

[42] Roddy Cowie and Randolph R Cornelius. Describing the emotional states that are expressed in speech. *Speech communication*, 40(1):5–32, 2003. Elsevier.

[43] Henriette Cramer, Nicander Kemper, Anne Zwijnenburg, and Ork de Rooij. Phobot: Hri'08 student design competition winner. In *Human-Robot Interaction (HRI), 2008 3rd ACM/IEEE International Conference on*, pages 375–382. IEEE, 2008.

[44] Elizabeth A Crane and M Melissa Gross. Effort-shape characteristics of emotion-related body movement. *Journal of Nonverbal Behavior*, 37(2):91–105, 2013. Springer.

[45] Charles Darwin, Paul Ekman, and Phillip Prodger. *The expression of the emotions in man and animals.* Oxford University Press, USA, 1998.

[46] Beatrice De Gelder. Why bodies? twelve reasons for including bodily expressions in affective neuroscience. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1535):3475–3484, 2009. The Royal Society Press.

[47] Marco De Meijer. The contribution of general features of body movement to the attribution of emotions. *Journal of Nonverbal Behavior*, 13(4):247–268, 1989. Springer.

[48] Bella M DePaulo. Nonverbal behavior and self-presentation. *Psychological bulletin*, 111(2):203, 1992. American Psychological Association.

[49] Amol Deshmukh, Aidan Jones, Srinivasan Janarthanam, Mary Ellen Foster, Tiago Ribeiro, Lee Joseph Corrigan, Ruth Aylett, Ana Paiva, Fotios Papadopoulos, and Ginevra Castellano. Empathic Robotic Tutors: Map Guide. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction Extended Abstracts*, pages 311–311. ACM, 2015.

[50] Matthieu Destephe, Miguel Brandao, Tatsuhiro Kishi, Massimiliano Zecca, Koji Hashimoto, and Atsuo Takanishi. Emotional gait: Effects on humans' perception of humanoid robots. In *Robot and Human Interactive Communication, 2014 RO-MAN: The 23rd IEEE International Symposium on*, pages 261–266. IEEE, 2014.

[51] Paul Ekman. Differential communication of affect by head and body cues. *Journal of personality and social psychology*, 2(5):726, 1965. American Psychological Association.

[52] Paul Ekman. An Argument for Basic Emotions. *Cognition and Emotion*, 6(34):169–200, 1992. Taylor & Francis.

[53] Paul Ekman and Richard J Davidson. *The nature of emotion: Fundamental questions.* Oxford University Press, 1994.

[54] Paul Ekman and Wallace V Friesen. Detecting deception from the body or face. *Journal of personality and Social Psychology*, 29(3):288, 1974. American Psychological Association.

[55] Rana El Kaliouby and Peter Robinson. Real-time inference of complex mental states from facial expressions and head gestures. In *Real-time vision for human-computer interaction*, pages 181–200. Springer, 2005.

[56] Péter Fankhauser and Jan Carius. Spherical rolling robot: A design and motion planning studies. *Robotics and Automation, IEEE Transactions on*, 16(6):835–839, 2000. IEEE.

[57] Joseph L Fleiss. Measuring nominal scale agreement among many raters. *Psychological Bulletin*, 76(5):378, 1971. American Psychological Association.

[58] Johnny Fontaine. Dimensional emotion models. In *The Oxford companion to emotion and the affective sciences*, pages 119–120. Oxford University Press, 2009.

[59] Johnny RJ Fontaine, Klaus R Scherer, Etienne B Roesch, and Phoebe C Ellsworth. The world of emotions is not two-dimensional. *Psychological science*, 18(12):1050–1057, 2007. SAGE Publications.

[60] Norman M Fraser and G Nigel Gilbert. Simulating speech systems. *Computer Speech & Language*, 5(1):81–99, 1991. Elsevier.

[61] NH Frijda, B Mesquita, and S. Van Goozen. The duration of affective phenomena, or emotions, sentiments and passions. *International Review of Emotion and Motivation*, pages 187–225, 1991. Springer.

[62] Nico H Frijda. *Moods, emotion episodes, and emotions.* Guilford Press, 1993.

[63] Viksit Gaur and Brian Scassellati. Which motion features induce the perception of animacy? In *Proc. 2006 IEEE International Conference for Development and Learning, Bloomington, Indiana*, pages 973–980. IEEE, 2006.

[64] Patrick Gebhard. Alma: a layered model of affect. In *Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems*, pages 29–36. ACM, 2005.

[65] Manuel Giuliani, Ronald Petrick, Mary Ellen Foster, Andre Gaschler, Amy Isard, Maria Pateraki, and Markos Sigalas. Comparing task-based and socially intelligent behaviour in a robot bartender. In *Proceedings of the 15th ACM on International conference on multimodal interaction*, pages 263–270. ACM, 2013.

[66] Erving Goffman. *On face-work: An analysis of ritual elements in social interaction*, volume 18. Taylor & Francis, 1972.

[67] R Gopinath. Employees' emotions in workplace. *Research Journal of Business Management*, 5(1):1–15, 2011. Scientific Research Publishing Company.

[68] Jonathan Gratch and Stacy Marsella. A domain-independent framework for modeling emotion. *Cognitive Systems Research*, 5(4):269–306, 2004. Elsevier.

[69] JA Gray and N McNaughton. The neuropsychology of anxiety. *British Journal of Psychology*, 69(4):417–434, 2009. Cambridge University Press.

[70] Hatice Gunes and Maja Pantic. Dimensional emotion prediction from spontaneous head gestures for interaction with sensitive artificial listeners. In *Intelligent virtual agents*, pages 371–377. Springer, 2010.

[71] Hatice Gunes, Caifeng Shan, Shizhi Chen, and YingLi Tian. Bodily Expression for Automatic Affect Recognition. *Emotion Recognition: A Pattern Analysis Approach*, pages 343–377, 2015. John Wiley & Sons, Inc.

[72] Kilem Li Gwet. *Handbook of Inter-Rater Reliability: The Definitive Guide to Measuring the Extent of Agreement Among Multiple Raters.* Advanced Analytics Press, 2012.

[73] Stephan Hamann. Mapping discrete and dimensional emotions onto the brain: controversies and consensus. *Trends in cognitive sciences*, 16(9):458–466, 2012. Elsevier.

[74] M Haring, Nikolaus Bee, and Elisabeth Andre. Creation and evaluation of emotion expression with body movement, sound and eye color for humanoid robots. In *The 20th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN, 2011 IEEE*, pages 204–209. IEEE, 2011.

[75] Eddie Harmon-Jones. Anger and the behavioral approach system. *Personality and Individual Differences*, 35(5):995–1005, 2003. Elsevier.

[76] Takuya Hashimoto, Sachio Hitramatsu, Toshiaki Tsuji, and Hiroshi Kobayashi. Development of the face robot SAYA for rich facial expressions. In *SICE-ICCAS, 2006. Society of Instrument and Control Engineers (SICE) - Institute of Control, Automation and Systems Engineers (ICASE) International Joint Conference*, pages 5423–5428. IEEE, 2006.

[77] Marcel Heerink, Krose Ben, Vanessa Evers, and Bob Wielinga. The influence of social presence on acceptance of a companion robot by older people. *Journal of Physical Agents*, 2(2):33–40, 2008. Red de Agentes Fisicos.

[78] Fritz Heider and Marianne Simmel. An experimental study of apparent behavior. *The American Journal of Psychology*, pages 243–259, 1944. JSTOR.

[79] Jochen Hirth, Norbert Schmitz, and Karsten Berns. Towards social robots: Designing an emotion-based architecture. *International Journal of Social Robotics*, 3(3):273–290, 2011. Springer.

[80] Laura Hoffmann and Nicole C Krämer. Investigating the effects of physical and virtual embodiment in task-oriented and conversational contexts. *International Journal of Human-Computer Studies*, 71(7):763–774, 2013. Elsevier.

[81] Tetsunari Inamura, Tomohiro Shibata, Hideaki Sena, Takashi Hashimoto, Nobuyuki Kawai, Takahiro Miyashita, Yoshiki Sakurai, Masahiro Shimizu, Mihoko Otake, Koh Hosoda, et al. Simulator platform that enables social interaction simulation - SIGVerse: SocioIntelliGenesis simulator. In *System Integration (SII), 2010 IEEE/SICE International Symposium on*, pages 212–217. IEEE, 2010.

[82] Minna Isomursu, Marika Tähti, Soili Väinämö, and Kari Kuutti. Experimental evaluation of five methods for collecting emotions in field settings with mobile applications. *International Journal of Human-Computer Studies*, 65(4):404–418, 2007. Elsevier.

[83] Carroll E Izard. *Human emotions*. Springer Science & Business Media, 1977.

[84] William James and George A Miller. *The Principles of Psychology vol 1, 2*. Harvard University Press, 2007.

[85] Michelle Karg, Ali-Akbar Samadani, Rob Gorbet, Kolja Kuhnlenz, Jesse Hoey, and Dana Kulic. Body movements for affective expression: a survey of automatic recognition and generation. *Affective Computing, IEEE Transactions on*, 4(4):341–359, 2013. IEEE.

[86] Michelle Karg, Mathias Schwimmbeck, K Kuhnlenz, and Martin Buss. Towards mapping emotive gait patterns from human to robot. In *The 19th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN, 2010 IEEE*, pages 258–263. IEEE, 2010.

[87] John F Kelley. An iterative design methodology for user-friendly natural language office information applications. *ACM Transactions on Information Systems (TOIS)*, 2(1):26–41, 1984. ACM.

[88] Cory D Kidd and Cynthia Breazeal. Effect of a robot on user perceptions. In *Intelligent Robots and Systems, 2004.(IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, volume 4, pages 3559–3564. IEEE, 2004.

[89] G Klein, David D Woods, Jeffrey M Bradshaw, Robert R Hoffman, and Paul J Feltovich. Ten Challenges for Making Automation a "Team Player" in Joint Human-Agent Activity. *Intelligent Systems*, 19(6):91–95, 2004. IEEE.

[90] Andrea Kleinsmith and Nadia Bianchi-Berthouze. Recognizing Affective Dimensions from Body Posture. In *Affective Computing and Intelligent Interaction*, pages 48–58. Springer, 2007.

[91] F. L. Krouse. Effects of pose, pose change, and delay on face recognition performance. *Journal of Applied Psychology*, 66(5):651–654, 1981. American Psychological Association.

[92] Barbara Kühnlenz, Stefan Sosnowski, Malte Buß, Dirk Wollherr, Kolja Kühnlenz, and Martin Buss. Increasing helpfulness towards a robot by emotional adaption to the user. *International Journal of Social Robotics*, 5(4):457–476, 2013. Springer.

[93] Rudolf Laban and Lisa Ullmann. *The mastery of movement.* ERIC, 1971.

[94] Brent Lance and Stacy C Marsella. Emotionally Expressive Head and Body Movement During Gaze Shifts. In *Intelligent virtual agents*, pages 72–85. Springer, 2007.

[95] J Richard Landis and Gary G Koch. The measurement of observer agreement for categorical data. *Biometrics*, 33(1):159–174, 1977. JSTOR.

[96] Quoc Anh Le, Souheil Hanoune, and Catherine Pelachaud. Design and implementation of an expressive gesture model for a humanoid robot. In *Humanoid Robots (Humanoids), 2011 11th IEEE-RAS International Conference on*, pages 134–140. IEEE, 2011.

[97] Iolanda Leite, Carlos Martinho, André Pereira, and Ana Paiva. iCat: an Affective Game Buddy Based on Anticipatory Mechanisms. In *Proceedings of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems-Volume 3*, pages 1229–1232. International Foundation for Autonomous Agents and Multiagent Systems, 2008.

[98] Iolanda Leite, Carlos Martinho, André Pereira, and Ana Paiva. As time goes by: Long-term evaluation of social presence in robotic companions. In *Robot and Human Interactive Communication, 2009. RO-MAN 2009. The 18th IEEE International Symposium on*, pages 669–674. IEEE, 2009.

[99] Robert W Levenson, Paul Ekman, and Wallace V Friesen. Voluntary Facial Action Generates Emotion-Specific Autonomic Nervous System Activity. *Psychophysiology*, 27(4):363–384, 1990. Wiley Online Library.

[100] Jacqyln A Levy and Marshall P Duke. The Use of Laban Movement Analysis in the Study of Personality, Emotional State and Movement Style: An Exploratory Investigation of the Veridicality of “Body Language”. *Individual Differences Research*, 1(1):39–63, 2003. Psychology and Behavioral Sciences Collection.

[101] Michael Lewis and Carolyn Saarni. *Lying and Deception in Everyday Life*. Guilford Press, 1993.

[102] Mei Yii Lim and Ruth Aylett. A New Approach to Emotion Generation and Expression. In *Proceedings of the Doctoral Consortium. The 2nd International Conference on Affective Computing and Intelligent Interaction*, pages 147–154. AAAC Press, 2007.

[103] K Liu and Rosalind W Picard. Embedded empathy in continuous, interactive health assessment. In *CHI Workshop on HCI Challenges in Health Assessment*, volume 1, page 3. ACM, 2005.

[104] Manja Lohse, Reinier Rothuis, Jorge Gallego-Pérez, Daphne E Karreman, and Vanessa Evers. Robot gestures make difficult tasks easier: the impact of gestures on perceived workload and task performance. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems*, pages 1459–1466. ACM, 2014.

[105] Maurizio Mancini, Ginevra Castellano, Christopher Peters, and Peter W McOwan. Evaluating the communication of emotion via expressive gesture copying behaviour in an embodied humanoid agent. In *Affective Computing and Intelligent Interaction*, pages 215–224. Springer, 2011.

[106] Robert P Marinier, John E Laird, and Richard L Lewis. A computational unification of cognitive behavior and emotion. *Cognitive Systems Research*, 10(1):48–69, 2009. Elsevier.

[107] Megumi Masuda and Shohei Kato. Motion rendering system for emotion expression of human form robots based on laban movement analysis. In *The 19th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN, 2010 IEEE*, pages 324–329. IEEE, 2010.

[108] Albert Mehrabian. *Basic Dimensions for a General Psychological Theory: Implications for Personality, Social, Environmental, and Developmental Studies*. Oelgeschlager, Gunn & Hain Cambridge Press, MA, 1980.

[109] Albert Mehrabian. Pleasure-Arousal-Dominance: A General Framework for Describing and Measuring Individual Differences in Temperament. *Current Psychology*, 14(4):261–292, 1996. Springer.

[110] Albert Mehrabian and James A Russell. A Verbal Measure of Information Rate for Studies in Environmental Psychology. *Environment and Behavior*, 1974. Sage Publications.

[111] François Michaud, Paolo Pirjanian, Jonathan Audet, and Dominic Létourneau. Artificial emotion and social robotics. In *Distributed autonomous robotic systems 4*, pages 121–130. Springer, 2000.

[112] Keith W Miller. It's not nice to fool humans. *IT professional*, (1):51–52, 2010. IEEE.

[113] Frederik Nagel, Reinhard Kopiez, Oliver Grewe, and Eckart Altenmüller. EMuJoy: Software for Continuous Measurement of Perceived Emotions in Music. *Behavior Research Methods*, 39(2):283–290, 2007. Springer.

[114] Toru Nakata, Tomomasa Sato, Taketoshi Mori, and Hiroshi Mizoguchi. Expression of Emotion and Intention by Robot Body Movement. In *Proceedings of the 5th International Conference on Autonomous Systems.* IEEE, 1998.

[115] Paula M Niedenthal. Emotion concepts. *Handbook of emotions*, 3:587–600, 2008. New York: The Guilford Press.

[116] Tatsuya Nomura, Takayuki Kanda, and Tomohiro Suzuki. Experimental investigation into influence of negative attitudes toward robots on human–robot interaction. *Ai & Society*, 20(2):138–150, 2006. Springer.

[117] Tatsuya Nomura and Kayoko Kawakami. Relationships between robot's self-disclosures and human's anxiety toward robots. In *Proceedings of the 2011 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology-Volume 03*, pages 66–69. IEEE Computer Society, 2011.

[118] Jekaterina Novikova, Swen Gaudl, and Joanna Bryson. Emotionally driven robot control architecture for human-robot interaction. In *Towards Autonomous Robotic Systems: 14th Annual Conference, TAROS 2013, Oxford, UK, August 28–30, 2013*, volume 8069, pages 261–263. Springer, 2014.

[119] Jekaterina Novikova and Leon Watts. Artificial emotions to assist social coordination in HRI. In *Workshop on Embodied Communication of Goals and Intentions at the International Conference on Social Robotics (ICSR'13)*, pages 31–38. ACM, 2013.

[120] Jekaterina Novikova and Leon Watts. A design model of emotional body expressions in non-humanoid robots. In *Proceedings of the Second International Conference on Human-Agent Interaction*, pages 353–360. ACM, 2014.

[121] Jekaterina Novikova and Leon Watts. Towards artificial emotions to assist social coordination in HRI. *International Journal of Social Robotics*, 7(1):77–88, 2015. Springer.

[122] Keith Oatley, Dacher Keltner, and Jennifer M Jenkins. *Understanding emotions.* Blackwell Publishing, 2006.

[123] Institute of Imaging&Computer Vision. Rwth - mindstorms NXT toolbox for MATLAB. http://www.mindstorms.rwth-aachen.de, 2013. Accessed: 2015-08-08.

[124] Dan R. Olsen and Stephen Bart Wood. Fan-out: Measuring human control of multiple robots. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '04, pages 231–238. ACM, 2004.

[125] Andrew Ortony, Gerald L Clore, and Allan Collins. *The Cognitive Structure of Emotions*. Cambridge university press, 1990.

[126] Andrew Ortony and Terence J Turner. What's basic about basic emotions? *Psychological review*, 97(3):315, 1990. American Psychological Association.

[127] Charles E Osgood. Dimensionality of the Semantic Space for Communication via Facial Expressions. *Scandinavian Journal of Psychology*, 7(1):1–30, 1966. Wiley Online Library.

[128] Ana Paiva, Joao Dias, Daniel Sobral, Ruth Aylett, Polly Sobreperez, Sarah Woods, Carsten Zoll, and Lynne Hall. Caring for Agents and Agents that Care: Building Empathic Relations with Synthetic Agents. In *Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems-Volume 1*, pages 194–201. IEEE Computer Society, 2004.

[129] Ana Paiva, Iolanda Leite, and Tiago Ribeiro. Emotion Modelling for Social Robots. In *The Oxford Handbook of Affective Computing*, pages 296–308. Oxford University Press, 2014.

[130] Jaak Panksepp. Toward a general psychobiological theory of emotions. *Behavioral and Brain sciences*, 5(03):407–422, 1982. Cambridge University Press.

[131] Samuel J Partington and Joanna J Bryson. The behavior oriented design of an unreal tournament character. In *Intelligent Virtual Agents*, pages 466–477. Springer, 2005.

[132] Catherine Pelachaud. Studies on gesture expressivity for a virtual agent. *Speech Communication*, 51(7):630–639, 2009. Elsevier.

[133] Catherine Pelachaud. *Emotion-Oriented Systems*. John Wiley & Sons, 2013.

[134] André Pereira, Carlos Martinho, Iolanda Leite, and Ana Paiva. icat, the chess player: the influence of embodiment in the enjoyment of a game. In *Proceedings*

of the 7th international joint conference on Autonomous agents and multiagent systems-Volume 3, pages 1253–1256. International Foundation for Autonomous Agents and Multiagent Systems, 2008.

[135] Rosalind W Picard and Roalind Picard. *Affective computing.* MIT Press, Cambridge, 1997.

[136] Robert Plutchik. A general psychoevolutionary theory of emotion. *Theories of emotion*, 1:3–31, 1980. Academic Press New York.

[137] Robert Plutchik. *The psychology and biology of emotion.* HarperCollins College Publishers, 1994.

[138] Aaron Powers, Sara Kiesler, Susan Fussell, and Cristen Torrey. Comparing a computer agent with a humanoid robot. In *2nd ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pages 145–152. IEEE Press, 2007.

[139] Kleinginna Paul R and Anne M Kleinginna. A categorized list of emotion definitions, with suggestions for a consensual definition. *Motivation and emotion*, 5(4):345–379, 1981. Springer.

[140] Robin Read and Tony Belpaeme. People interpret robotic non-linguistic utterances categorically. In *Proceedings of the 8th ACM/IEEE international conference on Human-robot interaction*, pages 209–210. IEEE Press, 2013.

[141] Robin Read and Tony Belpaeme. Situational context directs how people affectively interpret robotic non-linguistic utterances. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction*, pages 41–48. ACM, 2014.

[142] Byron Reeves and Clifford Nass. *How people treat computers, television, and new media like real people and places.* CSLI Publications and Cambridge university press, 1996.

[143] Tiago Ribeiro and Ana Paiva. The illusion of robotic life: principles and practices of animation for robots. In *Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction*, pages 383–390. IEEE, 2012.

[144] Charles Rich, Brett Ponsler, Aaron Holroyd, and Candace L Sidner. Recognizing engagement in human-robot interaction. In *Human-Robot Interaction (HRI), 2010 5th ACM/IEEE International Conference on*, pages 375–382. IEEE, 2010.

[145] Bob Ricks, Curtis W Nielsen, Michael Goodrich, et al. Ecological displays for robot interaction: A new perspective. In *Intelligent Robots and Systems,*

2004.(IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on, volume 3, pages 2855–2860. IEEE, 2004.

[146] Laurel D Riek. Wizard of oz studies in hri: A systematic review and new reporting guidelines. *Journal of Human-Robot Interaction*, 1(1), 2012. Public Knowledge Project.

[147] L.D. Riek and R.N.M. Watson. The age of avatar realism. *Robotics Automation Magazine, IEEE*, 17(4):37–42, 2010. IEEE.

[148] Tina L Robbins and Angelo S DeNisi. A Closer Look at Interpersonal Affect as a Distinct Influence on Cognitive Processing in Performance Evaluations. *Journal of Applied Psychology*, 79(3):341, 1994. American Psychological Association.

[149] Robotics-VO. A roadmap for u.s. robotics: From internet to robotics. https://robotics-vo.us/sites/default/files/2013%20Robotics%20Roadmap-rs.pdf, 2013. Accessed: 2015-08-08.

[150] James A Russell. A circumplex model of affect. *Journal of personality and social psychology*, 39(6):1161, 1980. American Psychological Association.

[151] James A Russell. Core affect and the psychological construction of emotion. *Psychological review*, 110(1):145, 2003. American Psychological Association.

[152] Gery W Ryan and H Russell Bernard. *Data management and analysis methods.* Sage Publications, 2000.

[153] Martin Saerbeck and Christoph Bartneck. Perception of affect elicited by robot motion. In *Proceedings of the 5th ACM/IEEE international conference on Human-robot interaction*, pages 53–60. IEEE Press, 2010.

[154] Jelle Saldien, Kristof Goris, Bram Vanderborght, Johan Vanderfaeillie, and Dirk Lefeber. Expressing emotions with the social robot Probo. *International Journal of Social Robotics*, 2(4):377–389, 2010. Springer.

[155] Klaus R Scherer. Neuroscience projections to current debates in emotion psychology. *Cognition & Emotion*, 7(1):1–41, 1993. Taylor & Francis.

[156] Klaus R Scherer. Psychological models of emotion. *The neuropsychology of emotion*, 137(3):137–162, 2000. Oxford University Press.

[157] Brian J Scholl and Patrice D Tremoulet. Perceptual causality and animacy. *Trends in cognitive sciences*, 4(8):299–309, 2000. Elsevier.

[158] Marc Schröder. Emotional speech synthesis: A review. In *Seventh European Conference on Speech Communication and Technology, INTERSPEECH*, pages 561–564. ISCA, 2001.

[159] Marc Schröder. Dimensional emotion representation as a basis for speech synthesis with non-extreme emotions. In *Affective dialogue systems*, pages 209–220. Springer, 2004.

[160] Azim F Shariff and Jessica L Tracy. What are Emotion Expressions For? *Current Directions in Psychological Science*, 20(6):395–399, 2011. Sage Publications.

[161] Mukesh Sharma, Dale Hildebrandt, Gem Newman, James E Young, and Rasit Eskicioglu. Communicating affect via flight path exploring use of the laban effort system for designing affective locomotion paths. In *Human-Robot Interaction (HRI), 2013 8th ACM/IEEE International Conference on*, pages 293–300. IEEE, 2013.

[162] Nancy C Sharts-Hopko. The coming revolution in personal care robotics: what does it mean for nurses? *Nursing administration quarterly*, 38(1):5–12, 2014. LWW.

[163] Bruno Siciliano and Oussama Khatib. *Springer handbook of robotics*. Springer Science & Business Media, 2008.

[164] Candace L Sidner, Cory D Kidd, Christopher Lee, and Neal Lesh. Where to look: a study of human-robot engagement. In *Proceedings of the 9th international conference on Intelligent user interfaces*, pages 78–84. ACM, 2004.

[165] Ashish Singh and James E Young. Animal-inspired human-robot interaction: A robotic tail for communicating state. In *Human-Robot Interaction (HRI), 2012 7th ACM/IEEE International Conference on*, pages 237–238. IEEE, 2012.

[166] Ashish Singh and James E Young. A dog tail for utility robots: exploring affective properties of tail movement. In *Human-Computer Interaction–INTERACT 2013*, pages 403–419. Springer, 2013.

[167] Aaron Sloman. How many separately evolved emotional beasties live within us. *Emotions in humans and artifacts*, pages 35–114, 2002. MIT Press.

[168] Mark Snyder. Self-monitoring of expressive behavior. *Journal of personality and social psychology*, 30(4):526, 1974. American Psychological Association.

[169] Stefan Sosnowski, Ansgar Bittermann, K Kuhnlenz, and Martin Buss. Design and evaluation of emotion-display eddie. In *Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference on*, pages 3113–3118. IEEE, 2006.

[170] SPARC. Strategic research agenda for robotics in europe 2014-2020. http://www.eu-robotics.net/cms/upload/PPP/SRA2020_SPARC.pdf, 2013. Accessed: 2015-08-08.

[171] Alexander Staller, Paolo Petta, et al. Introducing emotions into the computational study of social norms: A first evaluation. *Journal of artificial societies and social simulation*, 4(1):U27–U60. JASSS.

[172] Leila Takayama and Caroline Pantofaru. Influences on proxemic behaviors in human-robot interaction. In *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*, pages 5495–5502. IEEE, 2009.

[173] Janelle S Taylor. Cyborg babies: From techno-sex to techno-tots. *Medical Anthropology Quarterly*, 13(4):509–510, 1999. Wiley Online Library.

[174] Antonio Terracciano, Robert R McCrae, Dirk Hagemann, and Paul T Costa. Individual difference variables, affective differentiation, and the structures of affect. *Journal of personality*, 71(5):669–704, 2003. Wiley Online Library.

[175] Robert E Thayer. *The origin of everyday moods*. New York: Oxford University Press, 1996.

[176] Elena Torta, Johannes Oberzaucher, Franz Werner, Raymond H Cuijpers, and James F Juola. Attitudes towards socially assistive robots in intelligent homes: results from laboratory studies and field trials. *Journal of Human-Robot Interaction*, 1(2):76–99, 2012. Public Knowledge Project.

[177] Juan David Velásquez. *When Robots Weep: a Computational Approach to Affective Learning*. PhD thesis, Massachusetts Institute of Technology, 2007.

[178] K. Verfaillie and L. Boutsen. A corpus of 714 full-color images of depth-rotated objects. *Perception and psychophysics*, 57(7):925–961, 1995. Springer.

[179] R Walk and K Walters. Perception of the smile and other emotions of the body and face at different distances. In *Bulletin of the Psychonomic Society*, volume 26, pages 510–510. Psychonomic Society Inc, 1710 Fortview Rd, Austin, TX 78704, 1988.

[180] Harald G Wallbott. Bodily expression of emotion. *European journal of social psychology*, 28(6):879–896, 1998. Wiley Online Library.

[181] Astrid Weiss. *Validation of an evaluation framework for human-robot interaction: the impact of usability, social acceptance, user experience, and societal impact on collaboration with humanoid robots*. PhD thesis, University of Salzburg, 2010.

[182] Sarah Woods, Michael Walters, Kheng Lee Koay, and Kerstin Dautenhahn. Comparing human robot interaction scenarios using live and video based methods: towards a novel methodological approach. In *Advanced Motion Control, 2006. 9th IEEE International Workshop on*, pages 750–755. IEEE, 2006.

[183] Junchao Xu, Joost Broekens, Koen Hindriks, and Mark A Neerincx. Robot mood is contagious: effects of robot body language in the imitation game. In *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*, pages 973–980. ACM, 2014.

[184] Kimitoshi Yamazaki, Ryohei Ueda, Shunichi Nozawa, Mitsuharu Kojima, Kei Okada, Kiyoshi Matsumoto, Masaru Ishikawa, Isao Shimoyama, and Masayuki Inaba. Home-assistant robot for an aging society. *Proceedings of the IEEE*, 100(8):2429–2441, 2012. IEEE.

[185] Haris Zacharatos, Christos Gatzoulis, and Yiorgos L Chrysanthou. Automatic Emotion Recognition Based on Body Movement Analysis: a Survey. *Computer Graphics and Applications*, 34(6):35–45, 2014. IEEE.

[186] Massimiliano Zecca, Yu Mizoguchi, Keita Endo, Fumiya Iida, Yousuke Kawabata, Nobutsuna Endo, Kazuko Itoh, and Atsuo Takanishi. Whole body emotion expressions for KOBIAN humanoid robot–preliminary experiments with different emotional patterns. In *Robot and Human Interactive Communication, 2009. RO-MAN 2009. The 18th IEEE International Symposium on*, pages 381–386. IEEE, 2009.

[187] Zhihong Zeng, Maja Pantic, Glenn Roisman, Thomas S Huang, et al. A survey of affect recognition methods: Audio, visual, and spontaneous expressions. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 31(1):39–58, 2009. IEEE.